A Treatise on Downside Risk

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(ABSTRACT)

This dissertation is comprised of two papers. The first paper (Chapter 1) provides the theoretical foundation for the estimation of systematic downside risk. Using a new approach, I derive a measure of downside systematic risk, downside beta, that is free of the endogeneity problem and thus straightforward to calculate. Since there is no consensus in the literature regarding the appropriate method for the estimation of downside beta, I review the alternative specifications proposed in the past. I explicitly show that the derived formula here is more efficient in capturing downside risk on both theoretical and empirical grounds.

Using this efficient specification of systematic downside risk, I show that downside beta has increased explanatory power towards the cross-section of equity returns as compared to unconditional beta. In particular, downside beta predicts larger and more significant future premia, insignificant intercepts in portfolio cross-section tests and cannot be subsumed by additional risk factors proposed in the past literature. I attribute this superior performance of downside beta to its ability to capture distress risk and to the fact that it does not penalize (reward) good (bad) events in good states, as unconditional beta does.

In the second paper (Chapter 2) that is co-authored with my advisor, Gregory Kadlec, we exploit the notion of downside risk to explain a long-withstanding market anomaly; the long-term stock return reversals. We show that downside betas of past losers are significantly greater than downside betas of past winners, and that the inclusion of downside beta in Fama-Macbeth regressions subsumes the reversal effect.

Keywords: downside risk, downside beta, asset pricing, stock reversals, contrarian effect, market efficiency

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Dedication

To my father, Theodoros, and my mother, Aikaterini.

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Chapter 1

On the Estimation of Systematic Downside Risk

Abstract

This paper discusses the appropriate methodology for the estimation of systematic downside risk and examines its ability to explain the cross-section of future returns. I examine several specifications of downside beta and find that the Hogan-Warren (1974) approach is the only one consistent with the original downside risk framework, as defined by Markowitz (1959), and state-preference theory.

Empirically, the Hogan-Warren downside beta dominates both its unconditional counterpart and the alternative specifications of downside beta, implying that the role of downside risk has been greatly underestimated in the past literature. Additionally, as opposed to unconditional beta, it (i) predicts significantly larger slopes and non-significant intercepts in portfolio cross-sectional tests and (ii) is not subsumed by size and changes in market value of equity that drives the priced component of book-to-market [Gerakos and Linnainmaa (2012)].

In the presence of asymmetries in the return distribution, the superior performance of downside risk is attributed to its ability to capture distress risk and to the adverse pricing of unconditional risk in good states, which penalizes favorable and rewards unfavorable events.

1.1 Introduction

The idea that investment risk is more closely related to unfavorable outcomes than the entire distribution of investment returns is first noted in Roy (1952) and formalized by Markowitz (1952, 1959). Despite its intuitive appeal, downside risk has received limited attention in the literature, due to the complexity of estimation in a portfolio setting and the relatively weak evidence regarding its ability to explain returns. This study addresses both issues by showing that: (i) in the special case of systematic risk, downside beta is as straight-forward to estimate as unconditional beta [i.e., CAPM beta] and (ii) when downside beta is properly defined, it has explanatory power that dominates its unconditional counterpart.

The complexity of the estimation of downside risk in a portfolio setting lies in the endogeneity of the downside variance-covariance matrix. In general, downside risk measures consider only those observations (returns) below a pre-specified threshold. Commonly used thresholds include zero, the risk-free rate, and the sample market mean. When evaluating the downside variance of a portfolio, the threshold criterion has to be applied to the portfolio return, rather than individual security returns. Therefore, the set of relevant observations for the estimation of portfolio downside variance depends on portfolio returns, which in turn depend on the weights of the assets in the portfolio. This gives rise to an endogenous downside variance-covariance matrix.

This study demonstrates that, in the special case of systematic downside risk, the "endogeneity problem" disappears at the limit. Starting with downside variance, as defined by Markowitz (1959), and using the standard assumption that every security is insignificantly small as compared to the market, it is shown that systematic downside risk (downside beta) becomes exogenous to asset weights. That is, in the special case of downside beta, the conditioning on the threshold return is applied only to the market, which plays the role of a state variable. The conditioning only on market returns reflects the relative importance of the market and a security in the context of a theoretical portfolio. The derived formula for downside beta coincides with the specification proposed by Hogan and Warren (1974), but the approach followed here is more general; as such it is free of any asset pricing model assumptions, and as a result, the derived formulas can be applied in any case the importance of the assets in the portfolio is disproportionally different.

The "endogeneity problem" has motivated several approaches to an operational measure of downside risk. Since there is no consensus in the literature, regarding the appropriate method for the estimation of downside systematic risk, I consider alternative specifications of systematic downside risk in the literature proposed by Estrada (2002) and Ang et al (2006), and compare them to the Hogan-Warren downside beta.[1] The scope of this analysis is to examine the differences between the approaches in the context of the downside risk framework, as defined by Markowitz (1959). I find that the Hogan-Warren specification of downside beta is more efficient in capturing systematic downside risk, since it is the only approach that neither ignores diversification benefits, nor violates state-preference theory.

Ang et al (2006) provide empirical support for downside risk in explaining cross-sectional returns, but it is somewhat tenuous. In particular, they find a significant positive relation between downside beta and future stock returns, but only after excluding stocks in the highest volatility quintile. Having established that the HW specification is the appropriate method for estimating downside systematic risk, it is of interest to examine its power in explaining the cross-section of future returns. I find that the HW downside beta predicts higher and more significant premiums than either ACX beta or unconditional beta. In particular, the predicted premiums from Fama-MacBeth (1973) regressions for individual securities are 5.9% (t-stat=2.40), 2.7% (t-stat=1.79), and 3.9% (t-stat=1.82) for the HW, ACX, and CAPM beta respectively. The empirical results imply that the role of systematic downside risk have been greatly underestimated in the past literature.

[1] Referred as Estrada, ACX and HW downside beta, thereafter.

Early cross-sectional tests of unconditional beta report results that are inconsistent with the traditional form of the Sharpe-Lintner capital asset pricing model. In particular, Black, Jensen and Scholes (1972), Miller and Scholes (1972), Blume and Friend (1973) and Fama and MacBeth (1973) find slopes that are lower that the observed market risk premia and intercepts that are higher than predicted by theory. I find that, for portfolios, downside beta predicts future premia that are, on average, 150-200 bps higher than those of unconditional beta and intercepts that are insignificantly different than zero.

Next, I examine the performance of downside beta with respect to additional risk factors proposed in the literature. Fama and French (1992) find that the size and book-to-market have increased explanatory power over the cross-section of equity returns and that these factors subsume the effect of unconditional beta on average returns. Due to data limitations on the book-to-market measure, I use the change in the market value of equity [$\Delta(ME)$] over the estimation period, instead, which according to Gerakos and Linnainmaa (2012) captures the predictive power of the book-to-market ratio. Consistent with the results of Fama and French (1992), I find that the future premium of unconditional beta becomes insignificant, once these factors are included in Fama-MacBeth regressions. However, the relationship between downside beta and future returns remains strongly significant in the presence these factors. In particular, for double sorted portfolios on size and $\Delta(ME)$, the downside beta premium is 8.7% (t-stat:

2.76) in multiple regressions [the respective coefficient is 6.9% (t-stat: 2.24) for double sorted portfolios on $\Delta(ME)$ and size.

The superior performance of downside beta with respect to these factors appears to be related to the ability of downside risk to capture distress risk. Distress risk, that is associated with the probability of a firm surviving adverse market conditions, can be viewed as an extreme case of downside risk that evaluates the performance of the security during these adverse conditions, defined as the market underperforming the threshold return. Fama and French (1996) suggest that size and book-to-market can proxy for distress risk that is priced on average, but is not captured by the market premium. Under Chan and Chen (1991), size per se is not an indicator of distress, while the change in the market value of equity is. Consistent with this view, the relative performance of unconditional and downside beta is similar with respect to the size factor, but the downside risk measure subsumes the effect of $\Delta(ME)$. It can be argued that downside beta would capture distress risk more efficiently than size and $\Delta(ME)$, and this is the reason it cannot be subsumed by these factors.

Finally, I discuss the potential sources of the superior empirical performance of downside beta as compared to its unconditional counterpart. Nantell and Price (1979) show that if the returns are jointly normally distributed, then the two frameworks are equivalent. In the presence of return distribution asymmetries, downside beta performs better, because unconditional risk measures, in good states, penalize (reward) favorable (unfavorable) events. This interpretation is closely aligned with the results of Kraus and Litzenberger (1976) regarding skewness preference and the empirical findings of Harvey and Siddique (1999, 2000) regarding the pricing of co-skewness.

Many studies focus on downside risk as a more appropriate measure of investment risk. Mao (1970), Porter (1974) and Nantell and Price (1979) provide evidence regarding the superiority of downside risk as a decision criterion. Hogan and Warren (1974) show that the theoretical structure of the traditional CAPM is retained if downside variance substitutes for unconditional variance. Bawa and Lindenberg (1977), Fishburn (1977) and Harlow and Rao (1989) develop more generalized models measuring risk as deviations from a "target" return. More recently, Estrada (2002, 2004) shows that downside risk measures have increased explanatory power in markets with excess skewness. Finally, Ang et al (2006) provide evidence that systematic downside risk is relevant to the cross-section of stock returns. My study reconciles and extends this line of inquiry, providing new evidence regarding the importance of downside risk in asset pricing.

1.2 Estimating Systematic Downside Risk

Downside risk measures are formally introduced in the asset pricing literature by Markowitz (1952, 1959). In his pioneering work on portfolio theory, he examines semivariance[2], as a plausible measure of risk, and acknowledges its advantages over unconditional variance, as being more closely related to unfavorable outcomes. However, he chooses unconditional variance for his famous risk-return framework, because of its simplicity and ease of calculation. Many years later, Markowitz (1991) would note that "*semivariance seems more plausible than variance as a measure of risk, since it is concerned only with adverse deviations*".

Downside risk measures appear to be more intuitively appealing than their unconditional counterparts, as they estimate risk by considering only returns below a pre-fixed threshold. Thus, they are more closely related to the potentiality of losses, in contrast to unconditional risk measures, that equally penalize upside and downside variation. Mao (1970) and Fishburn (1977) show that the downside risk framework is

[2] Semi-variance literally means half of variance (from the Latin pre-fix "semi"), which is the case when the return distribution is symmetric and the threshold return is equal to the mean. I use the term "downside variance" instead to describe downside variation under any arbitrary distribution and threshold return.

consistent with a typical agent, who is risk averse and risk neutral for outcomes below and over the threshold, respectively. Such preferences are represented by a utility function that is concave up to the threshold return and linear thereafter.

A kinked utility function is theoretically motivated by the notion of loss aversion that suggests that individuals are more sensitive to losses than gains [Kahneman and Tvesky (1979); Barberis et al (2001); Barberis and Huang (2008)]. In the presence of loss aversion, the separation of downside and upside variation is preferable, since the two components of risk are priced differently.

In addition to a more realistic representation of preferences, downside risk measures perform better, when the strict distributional assumptions that the unconditional risk framework imposes are not valid. Nantell and Price (1979) show that if the joint distribution between the market and the securities is bivariate normal, then the two frameworks are equivalent; however if the joint distribution is bivariate lognormal, significant differences arise [Price et al (1982)]. There is an extensive empirical literature that suggests that return distributions deviate from normality.[3] It follows that in the absence of normality, higher moments become relevant for the pricing of securities [see Kraus and Litzenberger (1976), Harvey and Siddique (2000) and Dittmar (2002)]. In such a setting, the downside risk can capture more efficiently

[3] Fama (1965), Affleck-Graves and MacDonald (1989) and Richardson and Smith (1991) summarize most empirical deviations from Normality.

the asymmetries that primarily concern investors (i.e. fat-tails of losses) than unconditional risk, without penalizing the ones that they regard as favorable (i.e. positive skewness).

On the other hand, the main drawback of downside risk is the complexity of its estimation in a portfolio setting. This is because for the estimation of portfolio downside variance the conditioning on the threshold return is applied to portfolio returns that depend on the asset weights. Thus, in contrast to unconditional covariance, which is fixed for any two assets, downside covariance is weight (portfolio) specific. This is referred to as the "endogeneity problem", as the downside variance-covariance matrix becomes endogenously dependent on the asset weights. This limitation complicates the formation of efficient portfolios, as the derivation of the efficient frontier is unattainable, unless one relies on an approximation or a mathematical algorithm.

An important result presented here is that, for the special case of systematic downside risk, downside beta becomes exogenous to asset weights at the limit. For downside beta the conditioning on the threshold return is applied only to market returns, reflecting the importance between the market and a security in the context of a theoretical portfolio. The significance of the result is apparent, as it means that downside beta is as straight-forward to estimate as unconditional beta.

To derive this result, we start with downside variance as formally defined by Markowitz (1959):

$$(\sigma_i^D)^2 = \frac{1}{T}\sum_{t=1}^{T}[min(0, R_{it} - R_T)]^2 \quad (1)$$

where, R_{it} is the return of asset i at period t,

R_T is the threshold return and

T refers to the total number of periods.

Similarly to the unconditional framework, the downside variance of a portfolio is defined as the weighted average of the downside covariances of its assets.

$$(\sigma_P^D)^2 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i \cdot w_j \cdot \sigma_{ij}^D \quad (2)$$

In turn, the downside covariance between any two assets in the portfolio is given by:

$$\sigma_{ij}^D = \frac{1}{T}\sum_{t=1}^{K}\left[(R_{it} - R_T) \cdot \left(R_{jt} - R_T\right)\right] \quad (3)$$

where w_i is the weight of asset i,

N is the number of assets in the portfolio P,

T refers to the total number of periods,

K refers to the number of periods that portfolio P underperforms the threshold return R_T.

According to (1) downside variance takes into account only observations for which the asset underperforms the threshold return. However in (3), the subset of the relevant observations for the estimation of downside covariance (K) depends on whether portfolio P underperforms the threshold return R_T. Now consider a theoretical two-asset portfolio that consists of all available stocks for securities i and j. Downside covariance can be written as:

$$\sigma_{ij}^D = \frac{1}{T}\sum_{t=1}^{T}\left[(R_{it} - R_T)\cdot\left(R_{jt} - R_T\right)\cdot 1_A\right], where\ 1_A = \begin{cases} 1 \ \ if\ w_i \cdot R_{it} + w_j \cdot R_{jt} < R_T \\ 0\ if\ w_i \cdot R_{it} + w_j \cdot R_{jt} \geq R_T \end{cases} \quad (4)$$

The use of the indicator function in (4) moves the conditioning outside the formula and allows for the summation over the total number of periods(T). The “endogeneity” problem is apparent in the indicator function, since the relevant observations for the estimation of downside risk depends of the asset weights. Now assume that in the context of our theoretical portfolio, security i is insignificantly small as compared to security j. At the limit, as $w_i \to 0$ and $w \to 1$, (4) can be rewritten as:

$$\sigma_{ij}^D = \frac{1}{T}\sum_{t=1}^{T}\left[(R_{it} - R_T)\cdot\left(R_{jt} - R_T\right)\cdot 1_A\right], where\ 1_A = \begin{cases} 1 \ \ if\ R_{jt} < R_T \\ 0\ if\ R_{jt} \geq R_T \end{cases} \quad (5)$$

Notice that in (5) downside covariance is no longer dependent on asset weights. In contrast, the conditioning criterion is applied only to the “large” asset j, reflecting its relative importance in the portfolio. Additionally, the “small” asset i defines the sign of downside covariance in these relevant ("bad") states. We can rewrite (5) without the indicator function, as:

$$\sigma_{ij}^{D} = \frac{1}{T}\sum_{t=1}^{T}\left[(R_{it} - R_T) \cdot min\left\{0, \left(R_{jt} - R_T\right)\right\}\right] \quad (6)$$

Similarly, consider a theoretical portfolio consisting of a security and the market. Exploiting the standard assumption that every security is insignificantly small as compared to the market, it follows that their downside covariance is given by (6), with the market replacing the "large" asset j. Consequently, downside covariance between an asset and the market and downside beta can be written as:

$$\sigma_{iM}^{D} = \frac{1}{T}\sum_{t=1}^{T}[(R_{it} - R_T) \cdot min\{0, (R_{Mt} - R_T)\}] \quad (7)$$

$$\beta_{i,HW}^{-} = \frac{\sum_{t=1}^{T}[(R_{it} - R_T) \cdot min\{0, (R_{Mt} - R_T)\}]}{\sum_{t=1}^{T}[min\{0, (R_{Mt} - R_T)\}]^2} \quad (8)$$

The derived formula in (8) coincides with the downside beta proposed by Hogan and Warren (1974). However, it is important to note that the approach followed here is far more general. Hogan and Warren (1974) derive their formula in the context of a downside asset pricing model as an equilibrium result, while here downside beta emerges as a limit result that stems from the relative importance of the two assets in the context of a theoretical portfolio. This has two important implications. First, my approach is free of any model assumptions (i.e. the efficiency of the market portfolio).

Second, the derived formulas can be used in any setting the importance (weight) between the two assets is disproportionally different.[4]

A more intuitive way to present the limit result derived above is by observing the relevant areas for the estimation of downside covariance for a two-asset portfolio (Figure 1). For an equally weighted portfolio (Fig.1A), the relevant area (i.e. where the portfolio underperforms the threshold return) includes the entire QIII (where both assets underperform) and two equally sized areas in QII and QIV (where the underperformance of the one asset is greater than the over-performance of the other). For a portfolio that is more heavily weighted on asset j (Fig.1B), the increase in the relevant importance of asset j is depicted by the movement of the boundary line, so as to include a greater (smaller) area, where asset j underperforms (outperforms) the threshold.

Finally, consider the case where the weight of asset i is insignificant (Fig. 1C). This case corresponds to downside covariance in (7) and summarizes the dynamics of downside beta. Asset j (the market) functions as a state variable and defines the relevant areas for the estimation of downside risk (QII and QIII; the states where the market underperforms the threshold return). In these states, an observation is risk increasing if the security (asset i) also underperforms the threshold return (QIII) and

[4] For example, consider the case of a large enough portfolio (i.e. mutual fund, hedge fund) evaluating new asset allocations. Then downside risk contributions can be estimated using (7). Notice that the approach is subject to an approximation error that is inversely proportional to the relative weight of the two assets.

FIGURE 1: Relevant Areas for the Estimation of Downside Covariance

The figure presents the relevant areas for the estimation of downside covariance for a two-asset portfolio under the original formula, as proposed by Markowitz, and the Estrada approximation. The threshold return has been set equal to zero. The highlighted area depicts the states for which the portfolio underperforms the threshold return. The deep grey color indicates the areas that are relevant according to the Estrada approach. Figure 1A refers to an equally weighted two-asset portfolio. Figure 1B refers to a two-asset portfolio that is more heavily weighted on asset j. Figure 1C refers to a two-asset portfolio for which the weight on asset i is insignificantly large as compared to the weight of asset j. The signs refer to the sign of downside covariance in the respective areas.

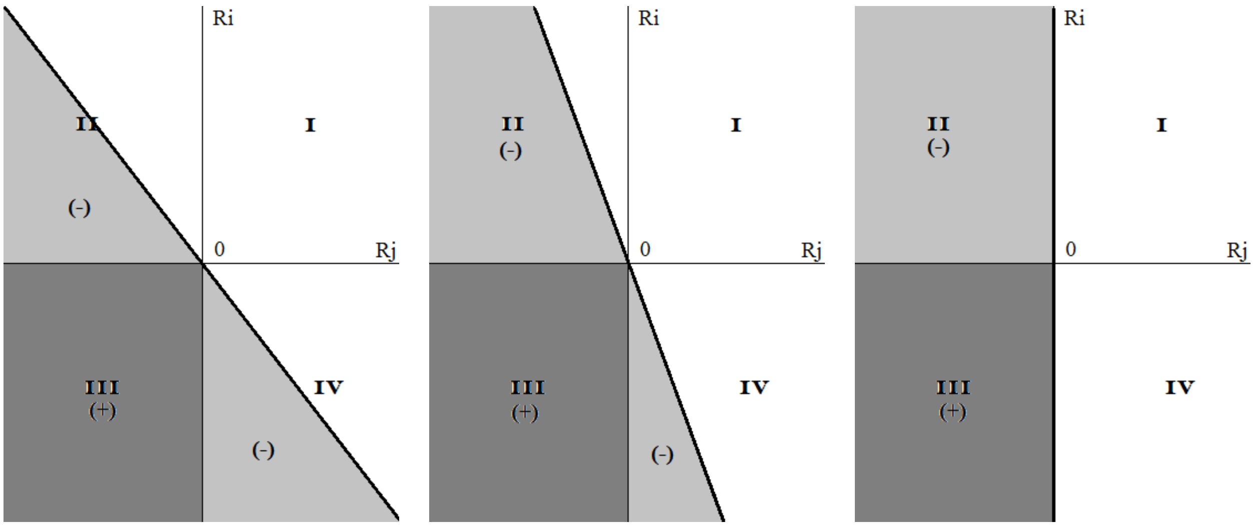

Figure 1A $x_i = 0.5, x_j = 0.5$

Figure 1B $x_i = 0.25, x_j = 0.75$

Figure 1C $x_i = 0.01, x_j = 0.99$

risk decreasing otherwise (QII). These dynamics are perfectly consistent with state-preference theory in the context of a framework where only bad states are relevant [see Arrow (1964); Debreu (1959)]. That is, when in an adverse state, defined by the market underperforming the threshold return, a bad event (i.e. the security also underperforming the threshold return) is contributing to risk, whereas a good event (i.e. the security overperfoming the threshold return) is highly desirable and risk-reducing.

1.3 Alternative Specifications of Downside Beta

The evaluation of the ability of systematic downside risk to explain the cross-section of equity returns requires that it is properly defined and estimated in the first place. However, there is no consensus regarding the appropriate methodology for the estimation of downside beta, since alternative specifications have appeared in the literature recently [Estrada (2002), Ang et al (2006)]. Therefore, it is important to examine and compare these methodologies and identify their differences.

Here, it is shown that both alternative specifications deviate from the original downside risk framework and violate state-preference theory in some states. Consequently, they are less effective in estimating systematic downside risk, which implies that the role of downside risk might be more important, than these approaches suggest. My results are consistent with the findings of an independent study by Post et al (2012), which also supports the HW specification, but the focus here is on the theoretical justification over the superiority of the Hogan-Warren approach.

In an effort to address the endogeneity problem, Estrada (2002) introduces a "heuristic approach", according to which downside covariance is estimated by considering only observations for which both assets underperform the threshold return. The rationale behind this method is simple; if both assets underperform the threshold return, then any combination (portfolio) of them will also underperform. Therefore, downside covariance becomes exogenous with respect to the weights of the assets in the portfolio.

The Estrada downside beta (β_{EST}^{-}) is defined as:

$$\beta_{i,EST}^{-} = \frac{\sum_{t=1}^{T}[min\{0,(R_{it} - R_T)\} \cdot min\{0,(R_{Mt} - R_T)\}]}{\sum_{t=1}^{T}[min\{0,(R_{Mt} - R_T)\}]^2} \quad (9)$$

Comparing (8) to (9), it is apparent that the main difference is that the Estrada downside beta additionally excludes the observations for which the security (asset i) overperforms the threshold return, in states where the market underperforms.

The differences between the two approaches are shown in Figure 1 that depicts the relevant areas for the estimation of downside covariance. The Estrada specification excludes any observation that lies outside QII (deep gray area), even if it appears relevant according to the original formula (light grey area). This has two important implications; first it reduces significantly the number of observations for the estimation of downside risk, which leads to higher estimation errors. Second and more importantly, the approach ignores the universe of risk-reducing observations. For these observations (depicted by light gray color in Fig.1) the two assets move in opposite directions with respect to the threshold return, yielding diversification benefits. As a result, downside risk is systematically overstated in the Estrada framework. The size of this overstatement depends on the correlation of the two assets, with the approach being less accurate, the less correlated the assets in the portfolio are, ceteris paribus.[5,6]

Another important drawback of this approach is that, the portfolio downside betas are strictly less than the weighted average downside betas of the individual securities, unless the assets are perfectly correlated.[7] This is because portfolio returns reflect diversification benefits that are ignored during the estimation of downside betas of individual securities. Therefore, at the portfolio level, the Estrada approach runs into the same "endogeneity problem" that it attempts to solve.

Ang et al (2006) use a different formula to estimate systematic downside risk. In their framework, downside beta is defined as the ratio of the conditional covariance between the security and the market over the conditional market variance.

$$\beta_{i,ACX}^{-} = \frac{Cov(R_i, R_M / R_M < R_T)}{Var(R_M / R_M < R_T)} \quad (10)$$

Comparing (10) to (8) both the HW and the ACX downside betas apply the conditioning criterion to market returns only. Thus, they use the same set of

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[5] The size of the overstatement also depends on the asset weights (in the general case) and the threshold return.
[6] It is trivial to show that $\beta_{i,EST} \geq \beta_{i,HW}$.
[7] The proof is available upon request.

observations for the estimation of downside beta. However, a closer inspection reveals important differences. In particular, (10) can be written as:

$$\beta_{i,ACX}^{D} = \frac{\sum_{t=1}^{T}\left[(R_{it} - \overline{R_i^*})\left(R_{Mt} - \overline{R_M^*}\right)/R_{Mt} < R_T\right]}{\sum_{t=1}^{T}\left[\left(R_{Mt} - \overline{R_M^*}\right)/R_{Mt} < R_T\right]^2} \quad (11)$$

where $\overline{R_i^*}$ and $\overline{R_M^*}$ refer to the conditional mean security and market returns over the observations that survive the conditioning criterion (i.e. market underperforms the threshold return).

From (11) it is apparent that the Ang et al (2006) approach involves two different threshold returns; the original threshold return (R_T) that is used for the conditioning and the conditional means ($\overline{R_i^*}$ and $\overline{R_M^*}$) that are used to measure risk deviations from. This methodological issue has a number of important implications for the consistency and the efficiency of (10) as an estimator of systematic downside risk.

The most important implication is the introduction of the "region-sign bias", which is clearly depicted in Figure 2. That is, in "mediocre bad states", - defined by the market return being lower than the original threshold but higher than the conditional market mean (areas A and D of Fig. 2C), the sign of risk contributions is the opposite of the expected. For these mediocre bad states, when the security overperforms the threshold return (area A) ACX downside beta is increased and when it underperforms (area D) ACX downside beta is decreased. This means that for the particular "region" (between the two thresholds), a positive event is considered undesirable (risk-increasing), while a negative event is considered desirable (risk-decreasing), which clearly violates state-preference theory. It is worth noting that this bias increases, the more extreme the performance of the security is.

FIGURE 2: Relevant Areas for the Estimation of Downside Beta

The figure presents the relevant areas for the estimation of downside beta under the three alternative specifications (Estrada (2002), Hogan-Warren (1974) and Ang, Chen and Xing (2006)). The threshold return and the conditional mean security return have been set equal to zero. Areas that increase (decrease) downside covariance/beta are depicted with a positive (negative) sign and deep (light) gray color. The red line in Fig.3C depicts the conditional market mean over the observations that survive the threshold return criterion.

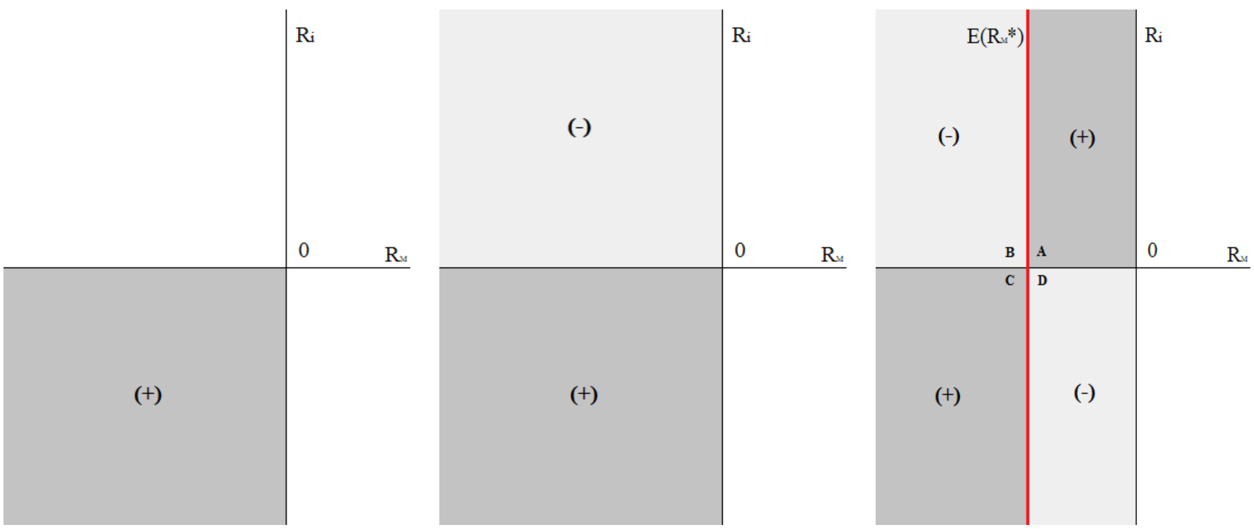


Figure 2A
Estrada Specification

Figure 2B
Hogan-Warren Specification

Figure 2C
Ang-Chen-Xing Specification

The source of the "sign region bias" is the use of covariance, which is a statistical measure of co-movement. Co-movement might make perfect sense when the entire range of returns is considered, since it is a measure of relative performance that matches good and bad states of the two assets. But when the returns of one of the assets are truncated, covariance can become uninformative or even misleading, because the “matching” of states no longer exists. In other words, when a bad state is defined (with respect to an asset), then it is the absolute and not the relative performance of the other asset that matters.

1.4 Methodology

The methodology of the empirical tests of this study follows the standard research design of the literature for cross-section tests. The main sample consists of all common stocks (share code 10 or 11) listed on the New York Stock Exchange (NYSE), American Stock Exchange (ASE), and Nasdaq from 1926 to 2010. I obtain monthly stock returns data from the Center for Research on Security Prices (CRSP). The equally weighted CRSP index serves as the proxy for the market portfolio. All reported returns are in excess of the one-month Treasury bill return. For the estimation of downside risk the threshold return is set equal to zero.[8]

The research setting consists of an estimation period (60 months) for the calculation of the risk measures followed by a test period (12 months) during which buy-and-hold future returns are calculated. The relationship between ex ante risk factors and future returns is examined in a set of Fama-MacBeth (1973) simple and multiple regressions of the form:

[8] In robustness test, I consider a sample consisting only of securities listed on NYSE, the value-weighted index as a market proxy and the market mean return as an alternative threshold return.

$$R_{it} = \gamma_0 + \gamma_{1t} \cdot Z_{it-1} + e_{it} \quad , i = 1,2, \ldots, N \;\; and \; t = 1,2, \ldots, T$$

where Z_{it-1} *is an ex ante risk factor (or a vector of risk factors).*

The cross-section regressions are estimated for every test period and then the time-series average coefficients and test statistics are reported.

For a security to be included in the analysis, it has to be continually listed for the estimation period, plus the first month of the test period.[9] If a security delists during the test period its delisting return (if available) is incorporated into the return of the last month and its nominal return is set equal to zero for the remaining of the test period. To increase the number of the observations and the power of the statistical tests, a one-year rolling window between estimation periods is used (80 estimation/test periods). I adjust for possible moving average effects, caused by the overlapping information, using Newey-West (1987) standard errors.

Following Blume (1970) and Black, Jensen and Scholes (1972), I also examine portfolios, in order to reduce estimation errors in risk variables by aggregating securities ("error-in-variables" problem). To avoid clustering positive and negative estimation errors, when securities are sorted on an estimated risk variable, i.e. unconditional beta, portfolios are formed in the period preceding the estimation of risk variables (formation period). This has two implications for our sample; first the number

[9] The requirement that return data for the first month of the test period exist ensures that the security is an available investment opportunity at formation date (security has not delisted during the last month of the estimation period).

of test period is reduced from 80 to 75 and the number of observations is reduced by nearly one third, since, in this case, securities have to be listed for a period of ten instead of five years. When the sorting variable can be estimated with no error (i.e. size), then portfolios are formed during the estimation period.

The methodology of this paper is similar to the research design of Ang et al (2006), but it differs in two important ways. First, the relationship between downside beta and future returns is examined over significantly longer test period; one-year instead of one-month future returns. This choice of a wider, future window appears appropriate in order to minimize microstructure biases [see Blume and Stambaugh (1983), Lo and MacKinley (1990)] and seasonal effects, as the January effect [see Keim (1983, 1989)] that are more pronounced in the short-term. Additionally, an extremely short test window fails to adequately quantify the impact of delistings, as delisted securities are removed from the sample almost immediately.[10] Second, this study uses the entire CRSP tape (1926-2010), instead of the shorter post-1962 period, examined by Ang et al (2006).

[10] Both considerations are expected to be more severe for downside risk [see Artavanis and Kadlec (2012)].

1.5 Empirical Results

1.5.1 Alternative Specifications of Downside Beta

The first part of this analysis examines the empirical differences between the alternative specifications of systematic downside risk, with focus on the ACX and HW downside beta. Table 1 offers a preliminary view of these differences. Panel A reports average means, percentiles and paired differences across periods. As expected, the Estrada approach assigns, on average, higher downside beta values to securities, since it overstates downside risk by ignoring risk-reducing observations. Interestingly, even though the HW and the ACX downside betas average to unity, the percentile analysis reveals that there is significant deviation between the two measures that distributes almost symmetrically around the median. For example, the mean paired difference of $\beta_{ACX}^{-} - \beta_{HW}^{-}$ is -0.25 (-0.57) for the 25^{th} (10^{th}) percentile and 0.29 (0.56) for the 75^{th} (90^{th}) percentile. However, the ACX downside beta appears to be higher than the already overstated Estrada measure for a considerable number of securities; the average paired difference for the 10th percentile is -0.19.[11] This finding is indicative of the inefficiency of the ACX measure, caused mainly by the "region-sign bias" discussed earlier.

TABLE 1: Summary Statistics of Risk Measures

The table presents summary statistics for the alternative specifications of downside beta. Means, medians and percentiles for risk measures and paired differences averaged across periods are reported in Panel A. Panel B reports average Pearson product moment correlations across periods between beta and the different specifications of downside beta for individual securities. In Panel C securities are sorted independently on quintiles based on their Hogan-Warren and Ang-Chen-Xing downside beta and then the percentage that falls in each of the 25 buckets is reported. The sample consists of all common stocks listed on NYSE, AMEX and NASDAQ for the period 1926-2010 (80 estimation periods).

Panel A: Summary Statistics

	Risk Measures			Paired Differences		
	β^-_{HW}	β^-_{ACX}	β^-_{EST}	$\beta^-_{EST}-\beta^-_{HW}$	$\beta^-_{EST}-\beta^-_{ACX}$	$\beta^-_{ACX}-\beta^-_{HW}$
Mean	*0.97*	*0.99*	*1.39*	*0.42*	*0.40*	*0.02*
Percentiles						
10th	0.33	0.22	0.72	0.12	-0.19	-0.57
25th	0.59	0.55	0.97	0.20	0.04	-0.25
Median	*0.93*	*0.94*	*1.32*	*0.33*	*0.31*	*0.03*
75th	1.31	1.39	1.74	0.53	0.66	0.29
90th	1.71	1.85	2.15	0.80	1.09	0.56

Panel B: Correlation Matrix of Risk Measures

	β	β^-_{HW}	β^-_{EST}	β^-_{ACX}
β	1	0.84	0.78	0.54
β^-_{HW}		1	0.83	0.72
β^-_{EST}			1	0.61
β^-_{ACX}				1

Panel C: Independent Sorts on Quintiles

	Low β^-_{ACX}	2	3	4	High β^-_{ACX}
Low β^-_{HW}	*59.89%*	21.88%	9.96%	5.70%	2.57%
2	26.65%	*36.83%*	21.58%	10.54%	4.40%
3	9.05%	27.11%	*32.68%*	21.80%	9.37%
4	3.16%	11.37%	26.68%	*35.57%*	23.23%
High β^-_{HW}	1.21%	2.85%	9.11%	26.43%	*60.40%*

[11] To be more precise, I find that, on average, the ACX downside beta is higher than the Estrada version for 23.2% of the securities, with the percentage ranging from 12% (1972-76) to 43% (1936-40).

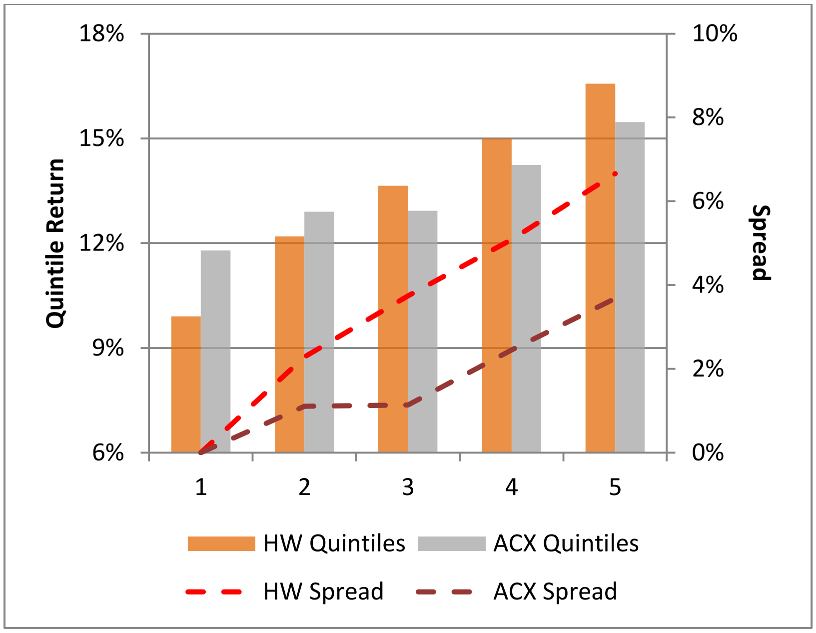
Panel B reports average correlations between unconditional beta and the three specifications of downside beta. The Hogan-Warren specification has the highest correlation with unconditional beta (corr: 0.84), consistent with the fact that downside beta is an almost truncated measure of unconditional systematic risk. By contrast, the correlation between the ACX specification and unconditional beta is remarkably low (corr: 0.54), and it appears only moderately correlated with the HW downside beta (corr: 0.72). Since the two approaches differ only with respect to the reference point for the estimation of risk deviations, it follows that the "region-sign bias" induces significant differences between them.

Panel C focuses on the relative differences between the HW and ACX downside betas by presenting independent sorts of individual securities to quintiles with respect to the two approaches. It is apparent that the main diagonal, excluding extremes, is considerably weak.[12] This means that the compared risk measures agree on the "broad" relative downside riskiness of the securities only for roughly 35% of the sample. Even in the extremes, where the diagonal elements are more pronounced, deviations are far from insignificant. For example, a stock that is marked as of the lowest downside risk level by the HW specification has over 8% probability to be regarded as highly risky by the ACX approach.

[12] Each quintile includes from 66 to 788 securities. Therefore, even a change to the next "risk bucket" (quintile) indicates a significant change in the ordering of the relative riskiness of the security.

<u>FIGURE 3:</u> Average Returns & Spreads for Quintiles Sorted on HW & ACX Downside Beta

The figure presents average returns across test periods for quintiles sorted on the Hogan-Warren and Ang-Chen-Xing downside beta. Dashed lines depict the spread from the lowest downside beta quintile. The sample consists of all common stocks listed on NYSE, AMEX and NASDAQ for the period 1926-2010 (80 estimation periods).



A preliminary view on the relationship of the HW and ACX downside betas with future returns is depicted in Figure 3, which reports average future returns for quintiles sorted on the two risk measures. Both approaches predict a positive future relationship, consistent with the hypothesis that investors demand a premium to bear systematic downside risk. However, the future spread for HW downside beta quintiles is significantly larger. In particular, the spread between the extreme HW quintiles is on average 6.67% (t-stat: 2.01) per annum. By contrast, the ACX predicts a significantly weaker positive relationship [the average spread is 3.68% (t-stat: 1.61)], consistent with the findings of Ang et al (2006).[13]

TABLE 2: FM regressions of Future Returns on HW and ACX Downside Beta

The table presents the results of Fama-MacBeth regressions of one-year test period returns on Hogan-Warren downside beta (β^{-}_{HW}) and Ang-Chen-Xing downside beta (β^{-}_{ACX}). Results for a sample consisting of all common stocks listed on NYSE, AMEX and NASDAQ and on NYSE only are reported in Panel A and Panel B respectively. Future returns are buy-and-hold returns. Cross-sectional regressions are estimated every year from 1931-2010, yielding 80 estimation/test periods. Average coefficients and Newey-West corrected t-statistics (in parenthesis) are reported. The Adjusted-R^2 is reported in the last row of each panel. Coefficients significant at the 10%, 5% and 1% level are denoted by (*), (**) and (***) respectively.

	Panel A: Full Sample			Panel B: NYSE stocks only		
Intercept	0.076***	0.108***	0.081***	0.073***	0.099***	0.077***
	(4.30)	*(5.22)*	*(4.49)*	*(4.45)*	*(4.95)*	*(4.62)*
$\boldsymbol{\beta^{-}_{HW}}$	**0.059****		**0.094****	**0.054****		**0.081****
	(2.40)		*(2.43)*	*(2.25)*		*(2.02)*
$\boldsymbol{\beta^{-}_{ACX}}$		0.027*	-0.039*		0.027*	-0.030
		(1.79)	*(-1.87)*		*(1.80)*	*(-1.34)*
Adj. R^2	0.036	0.016	0.042	0.039	0.018	0.047

Number of periods: 80, Number of observations: 157,266 (79,497)

Table 2 tests this future relationship more formally, using Fama-MacBeth regressions. HW downside beta predicts a significant future premium of 5.9% per annum (t-stat: 2.40). On the other hand, the ACX specification carries a positive, but marginally significant coefficient of 2.7% per annum (t:stat: 1.79). When both the HW and the ACX downside betas are included in the same regression, the former

[13] Ang et al (2006) find a significant relationship between their downside beta and future returns, only after excluding the top quintile of the most volatile stocks.

completely dominates the latter. The HW coefficient remains positive and strongly significant, while the ACX coefficient becomes significant, but with a reversed (negative) sign. These findings remain robust for a sample of securities listed on NYSE only (Panel B). Overall, the results indicate that the role of downside risk in explaining future returns is more important than Ang et al (2006) suggest.

1.5.2 Downside Beta and Unconditional Beta

Next, I examine the explanatory power of downside beta (Hogan-Warren downside beta thereafter) towards future returns, as compared to unconditional beta. Table 3 reports the results from Fama-MacBeth regressions of the two risk variables on future returns for individual securities and portfolios. Even in the case of individual securities (Panel A), systematic downside risk appears more strongly related to future returns, than unconditional risk. In particular, the predicted premium for downside beta is 5.9% (t-stat: 2.40), as opposed to a marginally significant premium of 3.9% (t-stat: 1.82) for traditional beta. When the two measures are included in the same regression, downside beta completely dominates its unconditional counterpart; its coefficient remains positive and strongly significant, while the coefficient of traditional beta becomes negative.

The portfolio results, presented in Panel B, become particularly interesting, when examined in relation to the findings of early tests of the Sharpe-Lintner model [see Black, Scholes and Jensen (1972), Miller and Scholes (1972), Blume and Friend (1973) and Fama and MacBeth (1973)]. These studies find that the use of unconditional beta in

TABLE 3: Fama-MacBeth regressions of Future Returns on Unconditional and Downside Beta

The table presents the results of Fama-MacBeth regressions of one-year test period returns on beta (β) and downside beta (β^-_{HW}). The analysis refers to individual securities (Panel A) and 20 portfolios per period, formed on the basis of their unconditional beta (Panel B) of the securities over the 5-year (formation) period preceding the estimation period. The sample consists of all common stocks listed on NYSE, AMEX and NASDAQ and future returns are buy-and-hold returns. Cross-sectional regressions are estimated every year and average coefficients and Newey-West corrected t-statistics (in parenthesis) are reported. The Adjusted-R^2 is reported in the last row of each panel. Coefficients significant at the 10%, 5% and 1% level are denoted by (*), (**) and (***) respectively.

	Panel A: Individual Securities			Panel B: Beta-sorted Portfolios		
Intercept	0.096***	0.076***	0.080***	0.047*	0.032	0.032
	(5.46)	*(4.30)*	*(4.73)*	(1.85)	(1.14)	(1.17)
$\boldsymbol{\beta}$	**0.039***		-0.025	**0.079****		-0.066
	(1.82)		*(-1.22)*	(2.44)		(-1.07)
$\boldsymbol{\beta^-_{HW}}$		**0.059****	**0.081*****		**0.096****	**0.165****
		(2.40)	*(3.00)*		(2.49)	(2.62)
Adj. $\boldsymbol{R^2}$	0.037	0.036	0.046	0.393	0.386	0.410
	Number of periods: 80, Number of observations: 157,266			*Number of periods: 75, Number of observations: 1500*		

cross-section tests yields significant intercepts and lower market risk premia than the ones empirically observed. These results cast doubt on the ability of traditional beta to effectively capture the notion of investment risk. Consistent with these findings, the results presented here show that unconditional beta predicts a relatively low premium [7.9% (t-stat: 2.44)] and a significant intercept. By contrast, downside beta not only predicts a larger and more significant premium [9.5% (t-stat: 2.63)], but also an intercept that is insignificantly different than zero.[14] These results remain strongly robust to alternative specifications of cross-sectional portfolio tests.[15]

1.5.3 Downside Beta and Additional Risk Factors

Motived by the weak relationship between average returns and unconditional beta, Fama and French (1992) find that size and book-to-market have increased explanatory power over the cross-section of equity returns. More importantly, they show that these factors subsume the effect of unconditional beta on average returns. Here, I re-examine these results in the presence of downside beta. Due to data limitations that the book-to-market measure imposes, I use the change in the market value of equity [$\Delta(ME)$] over the estimation period, instead. Gerakos and Linnainmaa (2012) show that changes in the market value of equity capture the predictive power of the book-to-market ratio.

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[14] Hogan and Warren (1974) prove that the structure of the traditional form of the capital asset pricing model is retained, if downside variance substitutes for unconditional variance, therefore enables us to make this comparison across the two frameworks.

[15] Table 3 refers to 20 portfolios per period. Table A1 (Appendix) presents results for 10 and 30 portfolios per period. Table 5 (Panel B3) refers to a sample that consists of securities listed on NYSE only, thus being more comparable with the sample of the studies mentioned before. Notice that for the NYSE sample, the slope of unconditional beta is even lower and the intercept is even higher. Both empirical failures of traditional beta are corrected in the presence of downside beta.

TABLE 4: Fama-MacBeth regressions of Future Returns in Double Sorted Portfolios

The table presents the results of Fama-MacBeth regressions of one-year test period returns on beta (β) and downside beta (β^{-}_{HW}), size and change in the market value of equity. Size is measured by the natural logarithm of the size of the firm in the last month of the estimation period. Changes in the market value of equity are measured over the five-year estimation period. The sample consists of all common stocks listed on NYSE, AMEX and NASDAQ and future returns are buy-and-hold returns. Cross-sectional regressions are estimated every year and average coefficients and Newey-West corrected t-statistics (in parenthesis) are reported. The Adjusted-R^2 is reported in the last row of each panel. Coefficients significant at the 10%, 5% and 1% level are denoted by (*), (**) and (***) respectively.

	Panel A: Double sorted portfolios on Size and Δ(ME)			Panel B: Double sorted portfolios on Δ(ME) and Size		
Intercept	0.324***	0.191***	0.178***	0.326***	0.214***	0.214***
	(4.07)	(2.84)	(2.80)	(4.09)	(3.97)	(3.79)
$\boldsymbol{\beta}$		0.072*			0.060	
		(1.84)			(1.58)	
$\boldsymbol{\beta^{-}_{HW}}$			**0.087*** **			**0.069** **
			(2.76)			(2.24)
Log_size	**-0.018*** **	**-0.012** **	**-0.012** **	**-0.018*** **	**-0.013*** **	**-0.014*** **
	(-3.05)	(-2.53)	(-2.46)	(-3.07)	(-3.14)	(-3.01)
$\boldsymbol{\Delta(ME)}$	**-0.016** **	**-0.017** **	-0.010*	**-0.016** **	**-0.017*** **	-0.010*
	(-2.28)	(-2.58)	(-1.73)	(-2.42)	(-2.70)	(-1.84)
Adj. $\boldsymbol{R^2}$	0.434	0.487	0.501	0.326	0.214	0.214
	Number of periods: 80, Number of observations: 2000					

Table 4 reports the results of multiple regressions for double sorted portfolios on size and $\Delta(ME)$. Both variables are highly significant when regressed on future returns [size coeff: -0.018 (t-stat:-3.05) and $\Delta(ME)$ coeff: -0.016 (t-stat: -2.28)]. Consistent with the results of Fama and French (1992), the future premium of unconditional beta becomes insignificant, once these factors are included in Fama-MacBeth regressions [7.2% (t-stat: 1.84) in Panel A and 6.0% (t-stat: 1.58) in Panel B]. However, the relationship between downside beta and future returns remains strongly significant in the presence of size and changes in the market value of equity. In particular, for double sorted portfolios on size and $\Delta(ME)$, the downside beta premium is 8.7% (t-stat: 2.76) in multiple regressions [the respective coefficient is 6.9% (t-stat: 2.24) for double sorted portfolios on $\Delta(ME)$ and size].

The ability of downside beta to survive the conditioning on these factors, as opposed to unconditional beta, stems mainly from the fact that downside risk can more efficiently subsume the effect of changes in the market value of equity. While unconditional and downside beta have a similar effect on the size factor, changes in the market value of equity become insignificant in the presence of systematic downside risk. A possible explanation for this result is provided by Fama and French (1996), who suggest that size and book-to-market can proxy for distress risk. Kapadia (2011) shows that distress risk commands a positive premium and can explain the effect of size and book-to-market in cross-sectional tests. Interestingly, Chan and Chen (1991), who introduce the notion of distress risk, show that changes in the market capitalization signal distress, while size per se is not necessarily an indicator of distress. These findings align with our empirical results in Table 4; if systematic downside risk can effectively capture distress, then it should have increased explanatory power towards changes in the market value of equity and a lesser impact on the size factor that does not necessarily indicate distress.

Distress risk refers to the risk that a firm is less likely to survive adverse economic conditions. Downside risk, on the other hand, measures the sensitivity of the stock's returns under adverse market conditions, defined as the market underperforming the threshold return. As such, distress risk can be viewed as an extreme case of downside risk; therefore downside beta is expected to have increased ability to capture it. Notice that the particular dynamics of the Hogan-Warren specification are perfectly aligned with the notion of distress; downside beta increases with poor stock performance in bad states, that might signal that the firm is in distress and decreases with good performance in bad states, which indicates strength and sovereignty.

1.5.4 Robustness Tests

The main results from the previous analysis remain strongly robust to different empirical settings. Table 5 presents the results of tests that examine the relationship between future returns, unconditional beta and downside beta [as in Table 3]. More specifically, I use the weighted-value index as a market proxy, the mean market excess return as an alternative threshold return and consider a sample that consists only of securities listed on NYSE for individual securities (Panel A) and beta-sorted portfolios (Panel B). Panel C reports the results for portfolios with fixed number of securities,

TABLE 5: Robustness Tests

The table presents the results of Fama-MacBeth regressions of one-year test period returns on unconditional beta (β) and downside beta (β^{-}_{HW}). The analysis refers to individual securities (Panel A) and to 20 portfolios per period (Panel B) or portfolios with a fixed number of securities (Panel C), formed on the basis of unconditional beta of the securities over the 5-year (formation) period preceding the estimation period (Panel B). In Panels A1 & B1 the value-weighted index is used as the market proxy. In Panels A2 & B2 the threshold return is set equal to the mean market return. In Panels A3 & B3 the sample consists of all common stocks listed on NYSE only. Future returns are buy-and-hold returns. Cross-sectional regressions are estimated every year and average coefficients and Newey-West corrected t-statistics (in parenthesis) are reported. The Adjusted-R^2 is reported in the last row of each panel. Coefficients significant at the 10%, 5% and 1% level are denoted by (*), (**) and (***) respectively.

	Panel A: Individual Securities								
	A1: Value-Weighted Index			A2: Market Mean Threshold			A3: NYSE Stocks Only		
Intercept	0.104***	0.083***	0.092***	0.096***	0.077***	0.079***	0.088***	0.073***	0.076***
	(5.89)	(4.45)	(5.29)	(5.46)	(4.33)	(4.68)	(5.36)	(4.45)	(4.98)
$\boldsymbol{\beta}$	0.024		-0.044**	0.039*		-0.027	0.037*		-0.022
	(1.42)		(-2.29)	(1.82)		(-1.25)	(1.81)		(-0.98)
$\boldsymbol{\beta^{-}_{HW}}$		**0.045****	**0.081*****		**0.059****	**0.083*****		**0.054****	**0.072****
		(2.37)	(3.26)		(2.23)	(2.90)		(2.25)	(2.48)
Adj. R^2	0.030	0.029	0.040	0.037	0.036	0.046	0.038	0.039	0.049

	Panel B: Beta-Sorted Portfolios								
	B1: Value-Weighted Index			B2: Market Mean Threshold			B3: NYSE Stocks Only		
Intercept	0.030	0.023	0.021	0.047*	0.032	0.032	0.052**	0.039	0.041*
	(1.01)	(0.78)	(0.70)	(1.85)	(1.14)	(1.17)	(2.19)	(1.57)	(1.71)
$\boldsymbol{\beta}$	**0.080****		0.014	**0.079****		-0.066	**0.071****		0.020
	(2.49)		(0.27)	(2.44)		(-1.07)	(2.27)		(0.34)
$\boldsymbol{\beta^{-}_{HW}}$		**0.091****	0.066		**0.096****	**0.165****		**0.085****	0.059
		(2.60)	(1.21)		(2.49)	(2.62)		(2.43)	(1.11)
Adj. R^2	0.378	0.372	0.404	0.393	0.386	0.410	0.356	0.355	0.383

	Panel C: Portfolios with Fixed Number of Securities					
	C1: Portfolios of 30 Securities			C2: Portfolios of 50 Securities		
Intercept	0.045*	0.025	0.023	0.047*	0.029	0.03
	(1.84)	(0.95)	(0.82)	(1.91)	(1.09)	(1.05)
$\boldsymbol{\beta}$	**0.082****		0.000	**0.079****		0.039
	(2.47)		(0.00)	(2.34)		(0.66)
$\boldsymbol{\beta^{-}_{HW}}$		**0.104*****	0.103*		**0.100****	0.057
		(2.73)	(1.89)		(2.58)	(0.90)
Adj. R^2	0.314	0.310	0.321	0.378	0.375	0.381

instead of fixed number of portfolios per period. Downside beta consistently predicts steeper slopes as compared to unconditional beta, and lower (insignificant in the case of portfolios) intercepts across all specifications.

1.6 The Superiority of Downside Beta: Discussion

The previous section provides compelling evidence regarding the superior performance of downside as compared to unconditional systematic risk in cross-section test; downside beta, using only a fraction of the observations, consistently predicts larger and more significant future premia, insignificant intercepts for portfolios and is not subsumed by additional risk factors. Therefore, it is of interest to discuss the reasons for the better performance of downside risk measures in the cross-section.

The main difference between unconditional and downside beta is that the latter ignores observations in good states – defined as the market outperforming the threshold return.[16] Under the assumption of joint normality the two frameworks (and risk measures) are equivalent, as shown by Nantell and Price (1979). But in the presence of asymmetries, significant differences emerge [see Price et al (1982)].

The past literature suggests that returns deviate from normality [see Fama (1965), Affleck-Graves and MacDonald (1989) and Richardson and Smith (1991)]. Thus, the

[16] Note that our robustness test (Table 5) suggest that our empirical results are extremely robust to the use of the market mean return as an alternative threshold.

crucial question is whether the difference in performance between downside and unconditional beta can be solely attributed to the existence of asymmetries in the return distribution. The high correlation between unconditional and downside beta (0.84) suggests it cannot. In other words, the distributional asymmetries do not appear to be large enough to induce the significant empirical differences we observed earlier. Therefore, there should be an additional cause that makes these "small" differences between the two risk measures, particularly important in cross-section tests.

Figure 4 presents the areas that command a premium (deep grey) or a discount (light grey) for downside beta, unconditional beta and co-skewness. Comparing the first two graphs, it becomes apparent that downside and unconditional beta price "bad states" – defined by the market underperforming the mean – in a similar way; favorable events (the security overperforming) command a discount and unfavorable ones (the security underperforming) command a premium. However in "good states", which are ignored for the estimation of downside beta, unconditional systematic risk increases with favorable and decreases with unfavorable events. Therefore, in "good states", unconditional beta "penalizes" desirable events and "rewards" undesirable events, resulting to the loss of efficiency of the unconditional measure.

FIGURE 4: Dynamics of Downside Beta, Unconditional Beta and Co-skewness

The figure presents the signs of the contributions to downside beta, unconditional beta and co-skewness of observations that lie in the respective areas and the corresponding -theoretically expected- premiums (deep grey areas) and discounts (light grey areas). The threshold return and the mean security return have been set equal to the mean market return to allow direct comparisons among the measures.

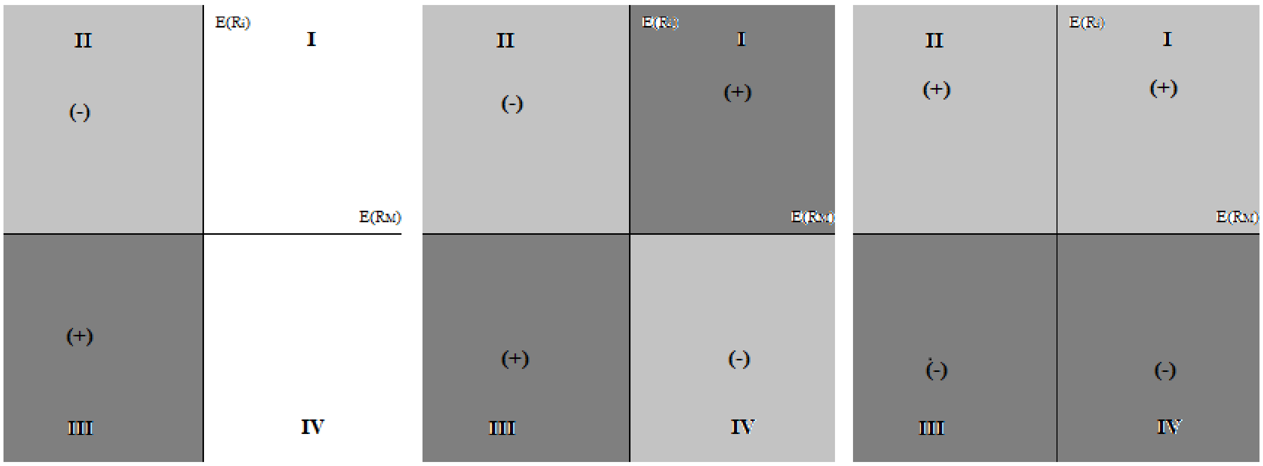

Figure 4A
Downside Beta

Figure 4B
Unconditional Beta

Figure 4C
Co-skewness

This sort of adverse pricing of unconditional risk in “good states” plays an important role to the difference in performance between the two risk measures. Notice that, as long as the joint normality assumption is valid, unconditional beta can efficiently proxy for downside beta, since observations symmetrically distribute around the means and the two states become equivalent. However, as asymmetries in the return distribution emerge, the two measures deviate and the adverse pricing of good states by unconditional beta becomes relevant.

This observation is closely related to the role of co-skewness[17] in the cross-section of equity returns. Kraus and Litzenberger (1976) suggest that investors with non-increasing risk aversion have a preference for positive skewness and an aversion for negative skewness, while Harvey and Siddique (2000) show that the premium for co-skewness is negative. Figure 4C presents the sign of co-skewness and its pricing dynamics. For "bad states" the pricing of co-skewness is aligned with the pricing of both downside and unconditional beta. However, in "good states" the pricing dynamics of co-skewness are exactly the opposite of those of unconditional beta.

In the context of the conditional version of the three-moment capital asset pricing model of Kraus and Litzenberger (1976), where both co-skewness (as gamma) and unconditional beta are included, the two risk variables exhibit opposite pricing dynamics in good states. This can explain the standard finding in the literature that the absolute magnitude of the gamma premium is significantly larger in positively as compared to negatively skewed markets.[18] In positively skewed markets, where "good states" become more important, gamma (standardized co-skewness) prices, not only the investors' skewness preference, but also corrects for the adverse pricing of unconditional beta.

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[17] Co-skewness of asset i is defined as, $Coskew_{i,t-1} = E_{t-1}[(r_i - E(r_i))(r_M - (E_M))^2]$.

[18] Smith (2007) finds that investors are willing to sacrifice 7.87% annually per unit of gamma in positively skewed markets, while they only demand a premium of 1.80% when the market is negatively skewed. Similarly, Harvey and Siddique (1999) find that a HML portfolio in co-skewness earns 5.00% annually when the market is positively skewed, but only 2.81% when the market is negatively skewed.

To conclude this discussion, the existence of asymmetries in the return distribution is a necessary condition for differences in performance between unconditional and downside beta to emerge. But the superior performance of downside risk is mainly due to the adverse pricing in good states by unconditional beta that becomes increasingly important the greater these asymmetries are.

1.7 Conclusions

Downside risk measures have received limited attention in the literature, mainly due to their complexity of estimation and the weak empirical results regarding their ability to explain returns. This paper uses a risk measure for the estimation of systematic downside risk that is increasingly efficient and consistent with state-preference theory, but most importantly, as easy to use and estimate as unconditional beta.

The study provides compelling evidence that downside systematic risk has increased power in explaining future returns and that its importance has been greatly underestimated in the past literature. Downside risk corresponds to more realistic approach of investor preferences, closely related with the notion of loss aversion. Additionally, it performs better when returns deviate from normality, as it focuses on adverse outcomes, without penalizing outcomes that might be regarded as favorable by the investors. Finally, it is closely related with distress risk, which can be regarded as a special case of downside risk

Chapter 2

Downside Risk and Long-Term Stock Return Reversals

Abstract

We argue that long-horizon return reversals [Debondt and Thaler (1985)] reflect a premium for downside risk. Consistent with this, we find that downside betas of past losers are significantly greater than downside betas of past winners, and the inclusion of downside beta in Fama-Macbeth regressions subsumes the reversal effect.

We note that downside risk offers a theoretical justification for the "distress risk" explanation for long-horizon return reversals of Fama and French (1996). Consistent with this view, we find that downside beta is more highly correlated with firm characteristics associated with distress (dividend reductions and delisting) and explains long-horizon return reversals better than SMB/HML and other proxies for distress risk in the literature.

2.1 Introduction

Long-horizon stock return reversals, the fact that stocks which performed poorly in prior years tend to outperform stocks that performed well in prior years, was first documented by DeBondt and Thaler (1985) in the context of U.S equities. More specifically, they found that stocks in the bottom decile of past five-year returns (losers) outperformed stocks in the top decile (winners) by more than 5% per annum during the subsequent five-year period. This reversal pattern exists for formation/test horizons of three to five years and is present in foreign equity markets as well [see Richards (1997), Baytas and Cakici (1999)]. The puzzle behind long-horizon return reversals is that this pattern does not appear to be explained by traditional measures of risk. Several studies attribute the contrarian pattern to investor overreaction, but it remains a subject of debate.[19]

The main insight of this paper is that downside risk can explain long-horizon return reversals in a manner that is consistent with market efficiency. Our central premise is

[19]For studies attributing the contrarian effect to investor overreaction, see Debondt and Thaler (1987), Chopra, Lakonishok, and Ritter (1992), and Lakonishok, Shleifer, and Vishny (1994).

that investors care about downside risk, earning returns below a certain threshold, rather than unconditional risk, and thus, demand a premium for bearing systematic downside risk.[20] This approach of defining risk based only on unfavorable outcomes is intuitively appealing, as initially noted by Markowitz (1959), and its relevance to asset pricing is supported by Ang, Chen and Xing (2006) who find a downside risk premium of approximately 6% per annum for U.S. equities.

Our empirical analysis finds that portfolios formed by sorting stocks on prior five-year returns, have a near monotonic ranking with respect to their formation-period downside betas. For example, the spread in downside beta between the loser and winner portfolios is 0.35 for terciles, 0.47 for quintiles, and 0.60 for deciles. By contrast, the spread in traditional beta is 0.09 for terciles, 0.12 for quintiles, and 0.13 for deciles. Given that the premium for systematic downside risk is of comparable magnitude to the market risk premium, the spread in downside betas appears more capable of explaining differences in the returns of loser and winner stocks than the spread in traditional beta.

A well-documented feature of long-horizon return reversals is that loser stocks outperform by more than winner stocks underperform. For example, for quintile portfolios, our sample loser stocks outperform by 6.1% per annum, while our sample

[20]Throughout the paper we refer to risk measures (i.e. beta, standard deviation) that are estimated across all outcomes as "unconditional" or "traditional" measures to clearly distinguish them from their downside counterparts.

winner stocks underperform by 3.2% per annum relative to the average stock for the five-year test period. The downside betas of losers and winners exhibit a similar asymmetry. For example, for quintile portfolios, downside betas of losers (1.26) are much higher than average (0.83), whereas downside betas of winners (0.79) are only slightly less than average. By contrast, traditional betas of losers (1.08) and winners (0.96) are both higher than average (0.82), and thus, do not appear capable of explaining the asymmetry in performance of winners and losers.

To more formally assess the role of downside risk in explaining contrarian profits (return differential between losers and winners), we form portfolios by ranking stocks on past returns. We then estimate annual Fama-Macbeth (1973) regressions of test period returns on formation-period returns and various risk measures. Consistent with DeBondt and Thaler (1985), long-horizon return reversals are both economically large and statistically significant for formation/test periods of three to five years. For example, the coefficient on past returns from simple regressions is -0.13 (t-stat: -2.28), -0.20 (t-stat: -2.11) and -0.23 (t-stat: -2.39) for three, four, and five-year test periods, respectively. Traditional beta accounts for roughly half of the reversal effect. More specifically, the coefficient on past returns is -0.06 (t-stat: -2.28), -0.08 (t-stat: -2.46) and -0.10 (t-stat: -2.46) when traditional beta is included in the regression. By contrast, downside beta accounts for almost all of the reversal effect. More specifically, the coefficient on past returns is -0.02 (t-stat: -1.17), -0.03 (t-stat: -1.88) and -0.05 (t-stat: -2.22) when downside beta is included in the regression. These results are robust to alternative empirical specifications common in the contrarian and downside risk literature, including stock sample, market portfolio proxy, method of handling delisted securities, and threshold return for estimation of downside risk.

Our study is related to several others that examine whether systematic risk is capable of explaining contrarian profits. DeBondt and Thaler (1985, 1987) find that losers tend to have lower betas than winners, and thus, systematic risk does not appear to be the source of contrarian profits. Chan (1988) and Ball and Kothari (1989) argue that formation-period betas are downward biased for loser stocks and upward biased for winner stocks, due to extreme (contrary) changes in leverage of losers and winners. Consistent with this, they find that betas of losers are significantly greater than betas of winners during the test period and that abnormal returns adjusted for test period betas do not differ significantly. However, inferences from test-period betas can be problematic due to "over-conditioning", which refers to the use of information that is not yet available [see Boguth et al (2011)]. Jones and Yoeman (2012) show that the over-conditioning bias in contemporaneous beta estimates of portfolios with extreme performance can be more important than the leverage effect. Additionally, the use of test period betas induces a severe survivorship bias in the analysis, since it implicitly excludes securities that delist during the test period. Our study shows that systematic risk can explain contrarian profits with an *ex ante* risk measure; downside beta.

Another intriguing aspect of downside risk is that it offers a theoretical justification for the "distress risk" explanation of the contrarian effect.[21] Chan and Chen (1991) provide evidence that loser stocks are more distressed than winner stocks. And as previously noted, the contrarian effect is driven primarily by the performance of loser stocks. Fama and French (1996) argue that the three-factor model explains the time-series returns of contrarian portfolios. They suggest that this is due to the ability of size and book-to-market to capture distress risk that appears to be more pronounced for losers and is not captured by the market factor. However, the contrarian effect of their sample period is quite different from that of the longer sample period typically examined in the literature. In particular, Fama and French (1996) find an insignificant reversal effect for the period 1963-1993, using the standard specification of the contrarian test period -- so they propose an alternative specification that skips a year between portfolio formation and test period. Moreover, the tendency for losers to outperform by more than winners underperform is all but absent from the 1963-1993 sample period [Table VI of Fama and French (1996)]. Therefore, the conclusion that the contrarian effect is driven by distressed firms (losers) is tenuous.

[21]Distress risk is a special case of downside risk. In particular, downside risk is the sensitivity of a stock's return to adverse market returns (i.e., less than risk-free rate) while distress risk is the sensitivity of stock's return to extreme adverse market outcomes (i.e., bankruptcies).

FIGURE 5: Return Spread of the Loser-Winner Portfolio

The figure presents the future 3-year return spread of the Loser minus Winner portfolio for the sample period from 1931 to 2011. Winners (Losers) are defined as the top (bottom) decile of securities sorted on their lagged five year returns. Dates refer to the beginning of the test period. Reported returns are monthly compounded returns in excess of the one month T-bill rate (buy-and-hold returns). The sample consists of all common stocks listed on NYSE.

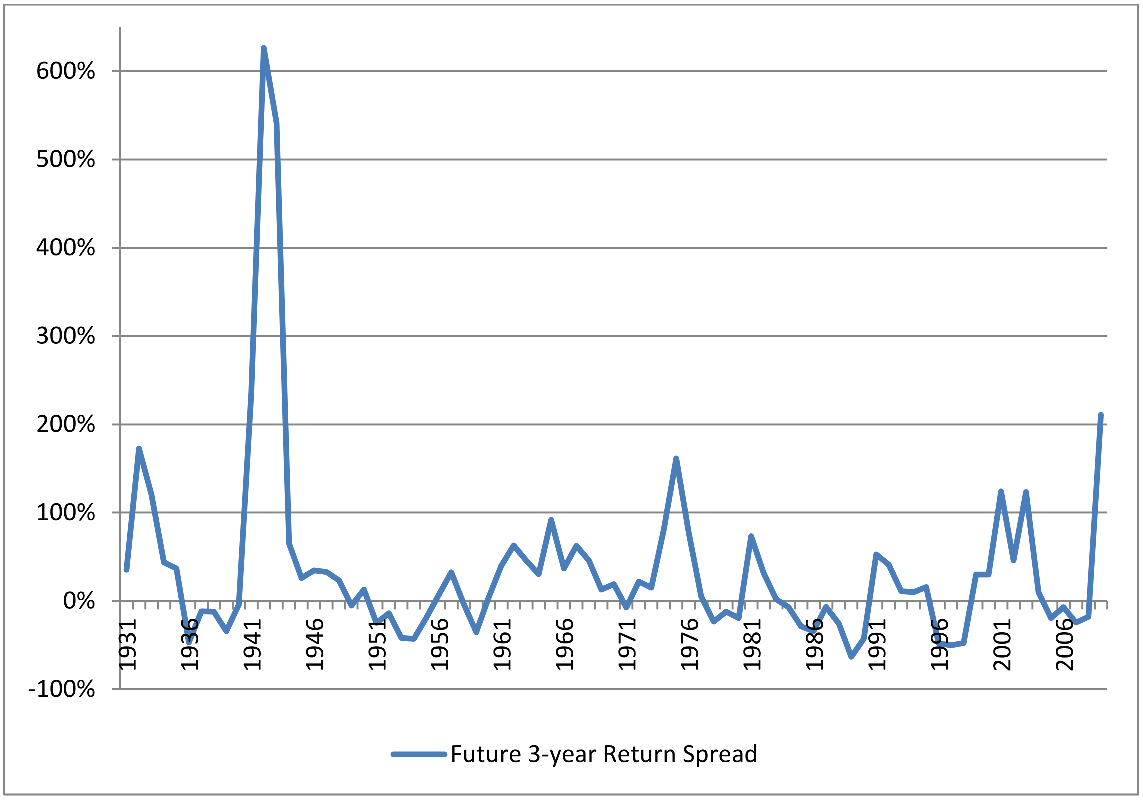

Figure 5 illustrates the importance of using a long sample period when evaluating the contrarian effect. More specifically, Figure 1 plots the three-year return spread of a zero cost portfolio of the loser decile minus the winner decile for the period 1931-2010. From Figure 1, it is evident that long-horizon return reversals vary substantially over time. As noted by Jones (1993), the returns of the contrarian portfolio tend to peak around important macro-events; the Great Depression, World War II, the Oil Crises.

Consistent with this observation, contrarian profits are also very large following the 2008 financial crisis, which indicates the continued relevance of the phenomenon.

We extend and refine the analysis of Fama and French (1996) by examining the relative merits of SMB and HML factors, a direct measure of distress risk proposed by Kapadia (2011), and downside risk in explaining contrarian profits over the period 1926-2010. Our analysis provides support for distress risk as an explanation for long-horizon return reversals, but we find that downside risk is more highly correlated with firm characteristics associated with distress (dividend reductions and delisting) and explains long-horizon return reversals better than SMB, HML, and direct measures of distress risk. Thus, it appears that either downside risk captures distress risk better than other proxies in the literature, or the contrarian phenomenon is driven by the more general notion of downside risk.

2.2 Downside Risk

The idea that investment risk is more closely related to unfavorable outcomes than the entire distribution of investment returns was first noted in Roy (1952) and formalized by Markowitz (1952, 1959). In addition to its intuitive appeal, the downside risk framework does not require restrictive assumptions regarding individuals' preferences (quadratic) or asset returns (Gaussian distribution). Two common measures of downside risk are the semi-variance, computed from observations below the mean, and the lower partial moment, computed from observations below a specified threshold return. These two specifications for downside risk are presented in Markowitz (1952) as:

$$(\sigma_i^D)^2 = E[min(0, R_{it} - RT)]^2 \quad (12)$$

where R_{it} *is the return of asset i during period t and RT is the threshold return (equal to the sample mean in the case of semi-variance).*

Downside risk has received limited attention in the literature due, in part, to the complexity of its estimation in a portfolio setting. The complexity arises from the fact that the threshold return criterion, which identifies the relevant observations for the estimation of downside risk, has to be applied to portfolio returns, rather individual security returns. As a result, the set of relevant observations for the estimation of portfolio downside variance depends on portfolio returns, which in turn depend on the weights of the assets in the portfolio. This gives rise to an endogenous downside variance-covariance matrix, which is dependent on individual asset weights.

The literature on downside risk includes several attempts to provide an operational measure of systematic downside risk [Hogan and Warren (1974), Estrada (2002) and Ang, Chen & Xing (2006)]. Artavanis (2012) shows that the Hogan-Warren specification follows directly from Markowtiz's (1959) definition of downside risk and is the only one consistent with state-preference theory.[22] Thus, we define downside beta, according to the Hogan-Warren specification, as:

$$\beta_i^D = \frac{\sigma_{iM}^D}{(\sigma_M^D)^2} = \frac{E\left[(R_{it} - RT) \cdot \left(min(0, R_{Mt} - RT)\right)\right]}{E[min(0, R_{Mt} - RT)]^2} \quad (13)$$

where R_{it} *is the return of asset i in period t,* R_{Mt} *is the return of the market in period t, and RT is the threshold return.*

[22]Artavanis (2012) shows that, when a security/portfolio is insignificantly small, as compared to the market, then Markowitz's downside covariance approaches the Hogan-Warren formula at the limit.

Note that, according to (13), the threshold criterion is applied only to the market return. Therefore, downside beta is free of the endogeneity problem, as the market return defines the relevant states for the estimation of downside risk. If a security outperforms (underperforms) the threshold in states where the market underperforms, then the observation is regarded as risk-decreasing (increasing). This approach to measuring downside systematic risk is consistent with state-preference theory, according to which when in a bad state (defined by the market), an unfavorable outcome is risk-increasing, while a favorable outcome is risk-decreasing.

2.3 Empirical Analysis

2.3.1 Data and Methodology

Our study examines the role of downside risk in explaining long-horizon return reversals. Our methodology follows the standard research design of the contrarian literature with some necessary adjustments to incorporate downside risk measures. Our main sample consists of all common stocks (share code 10 or 11) listed on the New York Stock Exchange (NYSE) from 1926 to 2010. We obtain monthly stock returns data from the Center for Research on Security Prices (CRSP) and monthly returns of the SMB and HML portfolios from the Kenneth R. French website. The equally weighted CRSP stock index serves as our proxy for the market portfolio. All reported returns are in excess of the one-month Treasury bill return and the threshold return for the estimation of downside risk measures is set equal to zero. In robustness tests, we examine an extended sample consisting of all common stocks listed on NYSE, AMEX and Nasdaq, the value-weighted CRSP stock index as the market proxy, and the market mean return as an alternative threshold criterion for downside risk.

Each year, we form equally weighted portfolios by sorting all stocks on past five-year returns (estimation period). We then track the portfolios' returns during the next three to five years (test period). Portfolio returns are calculated by averaging monthly compounded excess returns of individual stocks (buy-and-hold returns) for both the estimation and the test period. To avoid compounding single-period measurement biases, we use monthly compounded rather than cumulative excess returns as discussed in Conrad and Kaul (1993). To increase the number of observations, we use a one-year rolling window between estimation periods, which yields a total of 76 estimation/test periods. We adjust for possible moving average effects, caused by the overlapping information, using Newey-West (1987) standard errors.

For a security to be included in our analysis, we require that it have non-missing return data for the entire estimation period, and the first month of the test period.[23] To avoid survivorship bias, we do not exclude stocks that delist during the test period. If a stock delists during the test period its delisting return (when available) is incorporated into the return of the last month listed. Following Lakonishok, Shleifer, and Vishney (1994), the delisted stock's return for the remainder of the test period is set equal to the mean return of the portfolio through the end of the test period. This approach occupies a "middle ground" in the literature with respect to the handling of delisted stocks. A

[23]The requirement that return data for the first month of the test period exist ensures that the security is an available investment opportunity at formation date (security has not delisted during the last month of the estimation period).

more conservative approach assigns the return of the market to a stock following delisting [Ball et al., (1995)]. This understates the returns of losers, which tend to be riskier than the average stock. A more aggressive approach drops the stock altogether following delisting [DeBondt & Thaler (1985, 1987), Chan (1988)]. This overstates the returns of losers as it imparts a "rebalancing bias" [Keim and Stambaugh (1983)], which is greater for losers, since they delist more frequently. The results are qualitatively similar across the three approaches.

Our main empirical tests use the Fama-MacBeth (1973) cross-sectional and time-series regression methodology to examine the relation between future (test period) returns and past (formation period) returns and ex ante risk measures. More specifically, each year we estimate a cross-sectional regression (each with 20 portfolios) of the form:

$$R_{it} = \gamma_0 + \gamma_1 R_{it-1} + \gamma_2 RV_{it-1} + \epsilon_{it}$$

where R_{it} is portfolio i's test-period (three or five-year) return, R_{t-1} is the portfolio's formation period (past five-year) return and RV_{it-1} is a set of risk variables including: traditional beta, downside beta, and beta sensitivities to the SMB and HML portfolios and the Kapadia (2011) distress portfolio. We then compute the time-series average coefficients and the Newey-West corrected average t-statistics. As Fama and French (2008) note, the Fama-MacBeth (1973) methodology imposes a functional form between the dependent and independent variables. Following other studies of return reversals and asset-pricing, we use a linear specification for the relation between past returns and future returns.[24]

Before we proceed to the empirical results, we note two methodological challenges to our analysis of downside risk. First, cross-sectional asset pricing tests are subject to a bias caused by measurement errors in the estimation of beta, as noted by Black, Jensen, and Scholes (1972). This issue is more severe in the case of downside betas, which are estimated using roughly half the observations used to estimate traditional betas. One potential way to offset the reduction in observations for estimating downside risk is to use higher frequency data (daily vs monthly). However, high frequency data introduces substantial bias in beta estimates due to microstructure effects and the lead-lag adjustments for addressing this bias [Scholes and Williams (1977) and Dimson (1979)] are not valid in a setting where the time-series of observations is incomplete. Thus, following Black, Jensen, and Scholes (1972) we use portfolios, instead of individual stocks, in our analysis. Since the primary source of sampling error bias is the unsystematic component in returns, the formation of

[24] Asset-pricing tests typically use a linear specification for the relation between past returns and future returns to control for the reversal and the momentum effect [see Moskowitz and Grinblatt (1999), Ang et al (2006)]. We also use a logarithmic transformation of past returns and find that the coefficients decrease in magnitude, but not in statistical significance, consistent with the findings of Boyton and Oppenheimer (2006).

portfolios is expected to minimize its effect. Nevertheless, the fact remains that estimates of downside beta are noisier than estimates of traditional beta.

Our second challenge is the portfolio formation process. To address the "error-in-variables problem" Black, Scholes and Jensen (1972) suggest that the formation period should precede the estimation period, to avoid clustering positive and negative error terms. Due to the nature of the reversal phenomenon, which involves the performance of stocks between two consecutive periods, this methodology cannot be followed. Doing so would eliminate the variation in formation period returns that drive the reversal effect. However, it is important to note that the ranking criterion here is the past performance of stocks and not a risk variable. In unreported tests, we find that each portfolio, formed on the basis of past returns, includes securities that differ significantly with respect to their downside betas. For example, for 5x5 double-sorted portfolios, the spread in downside beta (high minus low downside beta portfolio) within each contrarian portfolio is greater than one. Therefore, the clustering of positive and negative errors is less plausible, since the formed portfolios include stocks with very different (downside) risk profiles.

2.3.2 Empirical Results

Table 6 provides an overview of average long-horizon return reversals, traditional beta, and downside beta for stocks sorted on past five-year returns across the seventy-six estimation/test periods. The right-hand portion of Table 6 depicts the reversal effect. A strong, negative relation between past returns and future returns is evident. Past losers significantly outperform past winners for up to five years after the portfolio formation date and this pattern is monotonic across portfolios. For extreme decile portfolios, losers earn 37.3%, 56.8% and 64.2% more than winners over the three, four and five-year period after portfolio formation. A well-documented feature of long-horizon return reversals is that loser stocks outperform by more than winner stocks underperform. We confirm this asymmetry in our sample. For example, for quintile portfolios, loser stocks outperform by 6.1% per annum, while winner stocks underperform by 3.2% per annum relative to the average stock for the five-year test period.

The left side of Table 6 reports the average traditional and downside betas of the portfolios. When risk is measured by traditional beta, losers appear to be only slightly riskier than winners. For example, the spread in traditional beta is 0.12 for quintiles and 0.13 for deciles. The small spread in traditional beta is largely consistent with the

TABLE 6: Average Risk Measures, Lagged and Future Returns

The table presents average values of beta, downside beta, lagged and future returns across estimation/test periods for quintiles and deciles formed by sorting stocks with respect to their lagged five-year returns. Extreme 50 portfolios are defined as the 50 top/bottom stocks per period with respect to their past five-year returns. Reported returns are monthly compounded returns in excess of the one month T-bill rate. Downside betas are estimated according to the Hogan-Warren (HW) specification. The sample consists of all common stocks listed on NYSE for the period 1926-2010 (76 estimation/test periods).

	Beta	Downside Beta	Lagged 5-year Returns	Future 3-year Returns	Future 4-year Returns	Future 5-year Returns
Quintiles						
Loser	1.08	1.26	-42.04%	59.35%	84.07%	103.10%
2	0.88	0.95	1.94%	47.06%	65.88%	82.96%
3	0.82	0.83	39.73%	39.58%	54.76%	68.89%
4	0.83	0.78	90.78%	37.52%	50.88%	63.13%
Winner	0.96	0.79	275.80%	30.43%	40.55%	51.79%
Loser-Winner	***0.12***	***0.47***	***-317.84%***	***28.92%***	***43.52%***	***51.31%***
Deciles						
Loser	1.17	1.40	-56.57%	66.40%	94.86%	112.00%
1	0.99	1.11	-27.58%	52.33%	73.32%	94.30%
2	0.90	0.99	-7.20%	50.22%	69.90%	86.80%
3	0.85	0.91	11.07%	43.88%	61.86%	79.14%
4	0.83	0.85	29.54%	39.72%	56.18%	71.01%
5	0.82	0.81	49.90%	39.44%	53.34%	66.78%
6	0.81	0.79	74.42%	39.11%	53.07%	65.22%
7	0.84	0.78	107.20%	35.93%	48.70%	61.03%
8	0.89	0.78	162.60%	31.75%	43.04%	55.81%
Winner	1.04	0.80	389.60%	29.10%	38.06%	47.78%
Loser-Winner	***0.13***	***0.60***	***-446.17%***	***37.30%***	***56.80%***	***64.22%***
Extreme 50						
Loser	1.25	1.53	-65.83%	68.03%	98.43%	114.50%
Winner	1.10	0.80	524.80%	26.63%	35.99%	46.00%
Loser-Winner	***0.15***	***0.73***	***-590.63%***	***41.40%***	***62.44%***	***68.50%***

findings of DeBondt and Thaler (1985), and appears incapable of accounting for the return differential of losers vs winners.[25] By contrast, when risk is measured by downside beta, losers are notably riskier than winners. For example, the spread in

[25] DeBondt & Thaler (1985) find a *negative* beta spread – that is winners have higher betas than losers. We attribute this finding to three factors; the sample period, the use of non-overlapping periods in their study and the use of cumulative instead of buy-and-hold excess returns.

downside beta is 0.47 for quintiles and 0.60 for deciles. Moreover, the asymmetry in the spread of downside betas aligns with the asymmetry in returns of losers vs winners. For example, downside betas of losers (1.26) are much higher than average (0.83) whereas downside betas of winners (0.79) are only slightly less than average. By contrast, traditional betas of both losers (1.08) and winners (0.96) are higher than average (0.82), and thus, do not appear capable of explaining the asymmetry in performance of winners and losers. While we cannot draw inferences regarding causality from these univariate statistics, the potential for downside risk as an explanation for long-horizon reversals is apparent in Table 6.

To formally assess the relative roles of traditional beta and downside beta in explaining long-horizon return reversals we estimate annual Fama-Macbeth (1973) regressions of test-period returns on formation-period returns and various risk measures with 20 portfolios per year. Our base specification consists of simple regressions of test-period returns on formation-period returns. We then include traditional beta and downside beta to examine their impact on the reversal effect.

Table 7 reports time-series average coefficient estimates and Newey-West corrected average t-statistics for each regression specification. The base specifications in Table 7 confirm the findings of DeBondt & Thaler (1985) of significant long-horizon return reversals. More specifically, the coefficient for past returns is -0.13 (t-stat: -2.28), -0.20 (t-stat: -2.11), and -0.23 (t-stat: -2.39) for three, four, and five-year test periods, respectively. The multivariate specifications examine whether systematic risk can

TABLE 7: Fama-MacBeth Regressions – Base Specification

The table presents Fama-MacBeth regressions of test period returns (three to five years) on beta (β), downside beta ($\beta_{Downside}$) and lagged five-year returns ($R_{t-1,t-60}$) for 20 portfolios per period, formed on the basis of their lagged returns. Future returns refer to buy-and hold returns in excess of the one month T-bill rate. The sample consists of all common stocks listed on NYSE. If a security delists during the test period, its delisting return is incorporated and its return is set equal to the mean portfolio return through the end of the test period. Cross-sectional regressions are estimated every year from 1931-2006, yielding 76 estimation/test periods. Average coefficients and Newey-West corrected t-statistics (in parenthesis) are reported. Coefficients significant at the 10%, 5% and 1% level are denoted by (*), (**) and (***) respectively.

	Fut. 3-year Returns			Fut. 4-year Returns			Fut. 5-year Returns		
Intercept	0.401***	0.102	0.048	0.544***	0.142	0.078	0.706***	0.218	0.179
	(5.30)	(0.77)	(0.29)	(5.73)	(0.69)	(0.31)	(6.22)	(0.86)	(0.61)
β		0.327*			0.452			0.528	
		(1.67)			(1.56)			(1.55)	
$\beta_{Downside}$			0.394*			0.538			0.588
			(1.70)			(1.60)			(1.54)
$R_{t-1.t-60}$	-0.132**	-0.055**	-0.017	-0.201**	-0.079**	-0.025*	-0.225**	-0.102**	-0.050**
	(-2.28)	(-2.28)	(-1.17)	(-2.11)	(-2.23)	(-1.88)	(-2.39)	(-2.46)	(-2.22)
Adj. R^2	0.242	0.430	0.436	0.245	0.397	0.404	0.250	0.400	0.412

explain the negative relation between past and future returns. The results suggest that the traditional beta can account for roughly half of the reversal effect. More specifically, the inclusion of traditional beta reduces the reversal coefficient to 0.06 (t-stat: -2.28), -0.08 (t-stat: -2.23), and -0.10 (t-stat: -2.46) for three, four, and five-year test periods, respectively. By contrast, downside beta accounts for almost all of the reversal effect. More specifically, the inclusion of downside beta reduces the reversal coefficient to -0.02 (t-stat: -1.17) -0.03 (t-stat: -1.88) and -0.05 (t-stat: -2.22) for the three, four, and five-year test periods, respectively.

TABLE 8: Fama-MacBeth Regressions -- Sub-period Analysis

The table presents Fama-MacBeth regressions of test period returns (one to five years) on downside beta ($\beta_{Downside}$) and lagged five-year returns ($R_{t-1,t-60}$) for 20 portfolios per period, formed on the basis of their lagged returns. The sample consists of all common stocks listed on NYSE. Cross-sectional regressions are estimated every year from 1931-1968 (38 test periods) and 1969-2006 (38 test periods). Average coefficients and Newey-West corrected t-statistics (in parenthesis) are reported. Coefficients significant at the 10%, 5% and 1% level are denoted by (*), (**) and (***) respectively.

Panel A: Subperiod 1931-1968

	Fut. 3-year Returns			Fut. 4-year Returns			Fut. 5-year Returns		
Intercept	0.534***	-0.062	-0.148	0.721***	-0.038	-0.159	0.926***	0.047	-0.049
	(4.50)	(-0.27)	(-0.47)	(5.06)	(-0.10)	(-0.34)	(5.56)	(0.10)	(-0.09)
β		0.628*			0.809			0.901	
		(1.89)			(1.59)			(1.51)	
$\beta_{Downside}$			0.725*			0.957			1.013
			(1.73)			(1.55)			(1.46)
$R_{t-1.t-60}$	-0.192*	-0.081**	-0.010	-0.302*	-0.122*	-0.027	-0.310*	-0.159**	-0.078**
	(-1.89)	(-2.03)	(-0.44)	(-1.73)	(-1.96)	(-1.47)	(-1.86)	(-2.19)	(-2.14)
Adj. R^2	0.215	0.384	0.390	0.218	0.341	0.349	0.208	0.339	0.353

Panel B: Subperiod 1969-2006

	Fut. 3-year Returns			Fut. 4-year Returns			Fut. 5-year Returns		
Intercept	0.269***	0.267**	0.245**	0.367***	0.322**	0.314**	0.485***	0.389*	0.407**
	(4.10)	(2.52)	(2.70)	(4.34)	(2.05)	(2.28)	(4.89)	(1.82)	(2.15)
β		0.025			0.095			0.155	
		(0.17)			(0.44)			(0.56)	
$\beta_{Downside}$			0.064			0.119			0.162
			(0.50)			(0.64)			(0.67)
$R_{t-1.t-60}$	-0.071	-0.030	-0.024	-0.101	-0.037	-0.024	-0.140*	-0.044	-0.022
	(-1.48)	(-1.16)	(-1.29)	(-1.58)	(-1.28)	(-1.19)	(-1.73)	(-1.53)	(-0.94)
Adj. R^2	0.269	0.475	0.481	0.273	0.453	0.460	0.292	0.460	0.470

As shown in Figure 5, the reversal effect varies substantially over time – being particularly pronounced following major macroeconomic events. Table 8 reports results for two sub-periods of equal length 1931-1968 and 1969-2006. Consistent with the findings of Jones (1993) and Boyton and Oppenheimer (2006) reversals are larger and more significant during the earlier sample period. From Table 8, the reversal coefficient for the five-year test period return is -0.31 (t-stat: -1.86) for the 1931-1968 sub-period and -0.14 (t-stat: -1.73) for the 1969-2006 sub-period.[26] As evident in Figure 5, the reversal effect of the recent sub-period is almost surely to increase with the inclusion of the 2008 financial crisis. We are unable to include the 2008 crisis in our analysis because the test period runs five years after portfolio formation. Nevertheless, the relative ability of traditional beta and downside beta to subsume the coefficient for lagged returns is nearly identical across these two sub-samples.

Thus far, our results show that downside risk largely subsumes long-horizon return reversals. A possible reason is that downside risk is more closely related to distress risk, which appears to be relevant to the contrarian effect. In particular, Chan and Chen (1991) provide evidence that loser stocks are more distressed than winner stocks. And as previously noted, the contrarian effect is driven primarily by the performance of loser stocks. To the extent that distress risk is not captured by market risk, it could explain the relatively higher returns of loser stocks. The Hogan-Warren specification of downside beta measures the sensitivity of a stock's return to adverse market returns (bad states) and thus, should have increased ability to capture distress risk relative to traditional beta.[27] Given that distress risk is a special case of downside risk (distress risk is focused on extreme adverse outcomes – such as bankruptcy), it is of interest to

[26] Coefficients and t-statistics should be interpreted with caution, due to the small number of observations in each sub-sample. Reversals during the latter sub-period appear much stronger with the rebalancing method or when the more extended sample consisting of common stocks listed on NYSE, AMEX and NASDAQ is examined.

[27] This is not entirely true for other specifications of downside beta [Estrada (2000), Ang, Chen, and Xing (2006)] that at times violate state-preference theory. For details, see Artavanis (2012).

examine the relative merits of distress risk and downside risk in explaining the contrarian effect.

Fama and French (1996) report that the three-factor model explains the time-series returns of contrarian portfolios. They attribute this result to the ability of size and book-to-market to capture distress risk. However, the contrarian effect is insignificant during their sample period (1963-1993) using the standard specification of the contrarian test period [Table VI of Fama and French (1996)]. Moreover, the tendency for losers to outperform by more than winners underperform is all but absent from their sample. So the conclusion that the contrarian effect is driven by distressed firms (losers) is tenuous. We extend and refine their analysis by examining the relative merits of SMB/HML, a direct measure of distress risk proposed by Kapadia (2011), and downside risk in explaining contrarian profits over the period 1926-2010.[28]

To examine the role of distress risk in explaining long-horizon return reversals, we use the aggregate distress risk tracking portfolios of Kapadia (2011) to estimate distress betas for the contrarian portfolios.[29] These tracking portfolios are formed as the linear combinations of size and book-to-market portfolios that ensure maximal correlation with future aggregate distress. The methodology, based on Lammont (2001), uses

[28] Our intent is not to replicate Fama French (1996), but rather to provide a direct test of their assertion that the contrarian effect is related to distress risk.
[29] The authors are grateful to Nishad Kapadia for making the distress risk tracking portfolio data available.

current market returns to predict future failure rates and exploits a unique dataset from Dun and Bradstreet that includes monthly failures of both public and private firms over the period 1894-1997. This approach is free of model assumptions and, most importantly, does not depend on accounting variables that limit other analyses of distress to the post-1963 period [see i.e., Vassalou and Xing (2004) and Campbell, Hilscher, and Szilagyi (2008)].

We estimate distress betas for each portfolio formed on the basis of lagged five-year returns by regressing its monthly returns on the monthly returns of the tracking portfolio over the estimation/formation period. Distress betas are typically negative, reflecting the negative relation between market returns and a hedge instrument against distress risk. In other words, the tracking portfolio returns are expected to be high (low), when firm failure rates are high (low) and stock returns are low (high). We also estimate size and book-to-market factor loadings for each portfolio using the monthly SMB and HML returns from the Kenneth R. French website.

Table 9 (Panel A) reports average estimates of traditional beta, downside beta, distress beta, SMB beta, HML beta, and various firm characteristics that the literature suggests are related to distress for quintiles of stocks sorted on lagged five-year returns. From Panel A, losers are on average one-third the market capitalization of winners. As Chan and Chen (1991) show size per se is not an indicator of distress; but rather it is the

TABLE 9: Distress Characteristics of Firms

Panel A presents average risk measures and firm characteristics of quintiles sorted on the basis of their past 5-year returns; traditional beta (β), downside beta ($\beta_{Downside}$), distress beta ($\beta_{Distress}$), size beta (β_{SMB}), book-to-market beta (β_{HML}), size, the percentage change in total dividends during the estimation period and. percentage of firms delisted within 5 years from the end of the estimation period. Distress beta is defined as the sensitivity of the portfolio returns on the returns of Kapadia's (2011) distress tracking portfolio in simple regressions. Similarly, size and book-to market betas are defined with respect to the monthly returns of the SMB and HML portfolios respectively. Size is estimated at the end of the estimation period and is in millions of dollars. Changes in dividends are winsorized at the 1% and 99% level. Panel B presents average Pearson product moment correlations between the risk measures and firm characteristics across 20 portfolios per period (time-series average taken over the estimation period). The sample consists of all common stocks listed on NYSE for the period 1927-2006.

Panel A: Firm Characteristics of Contrarian Portfolios

	β	$\beta_{Downside}$	$\beta_{Distress}$	β_{SMB}	β_{HML}	*Size*	Delistings	ΔDividends
Loser	1.08	1.25	-1.35	1.46	0.34	639.6	23.36%	-7.81%
2	0.88	0.95	-1.14	1.06	0.25	1,168.2	15.09%	32.26%
3	0.82	0.83	-1.09	0.95	0.25	1,482.9	12.76%	58.74%
4	0.83	0.78	-1.08	0.92	0.23	1,917.1	12.56%	88.78%
Winner	0.97	0.79	-1.16	1.15	0.14	2,115.1	12.24%	152.40%

Panel B: Correlation Matrix of Marginal Risk Characteristics (20 portfolios per period)

	β	$\beta_{Downside}$	$\beta_{Distress}$	β_{SMB}	β_{HML}	*Size*	Delistings	ΔDividends
β	1.00	0.80	-0.80	0.89	0.10	-0.44	0.50	-0.09
$\beta_{Downside}$		1.00	-0.69	0.80	0.14	-0.55	0.60	-0.46
$\beta_{Distress}$			1.00	-0.71	-0.41	0.43	-0.44	0.17
β_{SMB}				1.00	0.10	-0.57	0.53	-0.20
β_{HML}					1.00	-0.17	0.16	-0.24
Size						1.00	-0.38	0.27
Delistings							1.00	-0.33
ΔDividends								1.00

change in a firm's market capitalization. Thus, lagged five-year returns should provide a sort on distress. From Panel A, all five measures of risk are higher for loser portfolios than for winner portfolios. This relation is particularly strong for HML and downside risk where the progression is monotonic. Chan and Chen (1991) suggest that reductions in dividends proxy for cash flow and financing problems. Consistent with this, losers have experienced, on average, a reduction in dividends of 7.81% (21.52% for the sample that includes AMEX and Nasdaq stocks) during the five-year estimation period, whereas all of the other sample stocks experienced increases in dividends. The most direct evidence of the relative distress of loser vs winner firms can be seen by the fact that loser stocks delist (during the five year test period) twice as frequently as winner stocks, consistent with the findings of Chopra et al (1992) and Ball et al (1995). Though only suggestive, the asymmetry in delisting for losers vs winners (losers delist much more frequently than average whereas winners delist marginally less than average) aligns closely with the asymmetry in downside betas and return reversals of losers vs winners (see Table 6).

In Panel B we report the average correlations between the five risk measures and various firm characteristics associated with distress for 20 portfolios per period sorted on lagged five-year returns. Consistent with Fama and French (1996) and Kapadia (2011), SMB and HML are closely related to firm characteristics associated with distress. The correlation of SMB beta with dividend changes and delisting is -0.20 and 0.53, respectively. The correlation of HML beta with dividend changes and delisting is -0.24 and 0.16, respectively. It is interesting to note that collectively our evidence suggests that SMB is considerably more powerful than HML in capturing distress. SMB beta more is highly correlated with delisting and more highly correlated with both measures of distress risk -- downside beta and distress beta. From Panel B, the correlation of SMB beta with downside beta and distress beta is 0.80 and -0.71, respectively. By contrast, the correlation of HML beta –with downside beta and distress beta is 0.14 and -0.41, respectively. Finally, consistent with our hypothesis, downside risk appears to capture distress risk more efficiently than either SMB or HML. In fact, the correlation between downside risk and distressed firm characteristics are the highest of the five risk measures; the correlation between downside beta and dividend changes is -0.46, and between downside beta and delisting is 0.60.

We now turn to a formal analysis of the relative roles of distress beta, SMB beta, HML beta, and downside beta in explaining long-horizon return reversals. Our analysis replicates the Fama-MacBeth regressions of our main specification, using each of the measures of risk, but is constrained to a slightly shorter sample period 1927-2010, due to data limitations for our distress risk measure. Table 10 reports the results from the Fama-MacBeth regressions. As in the baseline regressions of Table 7, there is an economically large and statistically significant negative coefficient for lagged returns; -0.22 (t-stat: -2.35) for the five-year test period. Including the SMB and HML factor loadings in the regression (row II) reduces the coefficient of lagged returns by roughly half, but it remains significant; -0.10 (t-stat: -2.87). This is consistent with, but somewhat

TABLE 5: Fama-MacBeth Regressions – The Role of Distress Risk, SMB, and HML

The table presents the results of Fama-MacBeth regressions of five-year test period returns on lagged five-year returns ($R_{t-1,t-60}$), downside beta ($\beta_{Downside}$), distress beta ($\beta_{Distress}$), and SMB and HML factor loadings (β_{SMB} & β_{HML}). The analysis refers to 20 portfolios per period, formed on the basis of their lagged returns. The sample consists of all common stocks listed on NYSE. Cross-sectional regressions are estimated every year from 1932-2006 (76 estimation/test periods). Average coefficients and Newey-West corrected t-statistics (in parenthesis) are reported. The Adjusted-R^2 is reported in the last row of each panel. Coefficients significant at the 10%, 5% and 1% level are denoted by (*), (**) and (***) respectively.

Panel A: 4-year Test Period

	Intercept	$R_{t-1,t-60}$	β_{SMB}	β_{HML}	$\beta_{Distress}$	$\beta_{Downside}$	*Adj.* R^2
(I)	0.551***	-0.201**					0.247
	(5.64)	(-2.08)					
(II)	0.359***	-0.083**	-0.190	0.450			0.415
	(4.20)	(-2.55)	(-0.69)	(1.16)			
(III)	0.220	-0.071**			-0.313		0.361
	(1.20)	(-2.08)			(-1.47)		
(IV)	0.090	-0.027*				0.532	0.407
	(0.36)	(-1.94)				(1.56)	
(V)	0.160	-0.058**			-0.217	0.202	0.421
	(0.87)	(-2.11)			(-1.17)	(1.27)	
(VI)	0.16	-0.010	-0.430	0.590		0.608	0.432
	(1.13)	(-0.37)	(-0.91)	(1.23)		(1.22)	
(VII)	0.040				-0.118	0.477**	0.367
	(0.18)				(-0.80)	(2.22)	
(VIII)	0.150		-0.470	0.660		0.691*	0.419
	(1.11)		(-1.09)	(1.43)		(1.83)	

Panel B: 5-year Test Period

	Intercept	$R_{t-1,t-60}$	β_{SMB}	β_{HML}	$\beta_{Distress}$	$\beta_{Downside}$	*Adj.* R^2
(I)	0.709***	-0.223**					0.252
	(6.14)	(-2.35)					
(II)	0.432***	-0.103***	-0.063	0.398			0.434
	(3.21)	(-2.87)	(-0.31)	(1.30)			
(III)	0.295	-0.088**			-0.364		0.369
	(1.35)	(-2.15)			(-1.49)		
(IV)	0.191	-0.052**				0.578	0.414
	(0.64)	(-2.18)				(1.50)	
(V)	0.287	-0.086**			-0.303	0.137	0.429
	(1.33)	(-2.51)			(-1.41)	(0.76)	
(VI)	0.282	-0.049*	-0.279	0.538		0.465	0.452
	(1.59)	(-1.69)	(-0.82)	(1.41)		(1.21)	
(VII)	0.129				-0.096	0.582**	0.377
	(0.44)				(-0.56)	(2.44)	
(VIII)	0.206		-0.393	0.656		0.717*	0.438
	(1.05)		(-1.12)	(1.66)		(1.97)	

weaker than the evidence in Fama and French (1996), who find that SMB and HML subsume the long-horizon reversal effect over the 1963-1993 sub-period. The next specification (row III of Table 10) provides a direct test of Fama and French's (1996) assertion that the contrarian effect is related to distress risk by including distress beta in the regression. As with the case of the regressions with SMB ad HML, the coefficient of lagged returns is reduced by roughly half, but remains significant [-0.09 (t-stat: -2.15)]. Thus, the contrarian effect appears to be related to distress risk, but it is not completely subsumed by either SMB/HML beta or distress beta. The fact that distress beta and SMB/HML beta have similar power in explaining the reversal phenomenon is likely due to the fact that the tracking portfolios for distress risk are linear combinations of size and book-to-market portfolios.

The fourth specification confirms that downside risk provides the greatest explanatory power for reversal effect among the competing risk measures. From row IV of Table 10, the inclusion of downside beta reduces the coefficient of lagged returns to -0.03 (t-stat: -1.94) for the four-year test period and to -0.05 (t-stat: -2.18) for the five-year test period. In the last two specifications, it is shown that downside beta retains its significance in the presence of the alternative risk measures, when past returns are not included in the regression. Overall, our analysis provides direct evidence to confirm that distress risk plays an important role in long-term reversals and that downside risk either captures distress risk better than SMB/HML and distress beta or the reversal phenomenon is driven by the more general concern for downside risk.

2.3.3 Robustness and Additional Tests

In this section, we examine the robustness of our results to different methodological specifications common in the contrarian and downside risk literature. The first test examines the sensitivity of our results to the approach used for handling delisted stocks. This issue is potentially important in the context of the contrarian effect given the substantial difference in the incidence of delisting for losers and winners. In our main specification, when a stock delists during the test period its delisting return (when available) is incorporated into the return of the last month listed and the delisted stock's return for the remainder of the test period is set equal to the mean return of the portfolio through the end of the test period [as in Lakonishok et al (1994)].

As previously noted, the approach we use for handling delisting occupies a "middle ground" among alternative approaches used in the literature. A more conservative approach assigns the return of the market to a stock following delisting [Ball et al., (1995)]. This understates the returns of losers, which tend to be riskier than the average stock. We repeat the analysis of Table 7 using the more conservative approach. We do not tabulate the results because they are very similar to those of Table 7. More specifically, we find that under the more conservative approach the reversal effect is reduced slightly, but remains significant and our inferences regarding the inclusion of traditional and downside beta remain unchanged.[30] A more aggressive approach drops the stock altogether following delisting [DeBondt & Thaler (1985, 1987), Chan (1988)]. This overstates the returns of losers as it imparts a "rebalancing bias" [Keim and Stambaugh (1983)], which is greater for losers, which delist more frequently. These results do differ somewhat from Table 7 and are reported in Table 11.

TABLE 11: Robustness Tests - Rebalancing Method

The table presents Fama-MacBeth regressions of test period returns (one to five years) on downside beta ($\beta_{Downside}$) and lagged five-year returns ($R_{t-1,t-60}$) for 20 portfolios per period, formed on the basis of their lagged returns. The sample consists of all common stocks listed on NYSE and portfolios are rebalanced monthly. Cross-sectional regressions are estimated every year from 1931-2006 (76 test periods). Average coefficients and Newey-West corrected t-statistics (in parenthesis) are reported. Coefficients significant at the 10%, 5% and 1% level are denoted by (*), (**) and (***) respectively.

	Fut. 3-year Returns			Fut. 4-year Returns			Fut. 5-year Returns		
Intercept	0.409***	-0.080	-0.144	0.569***	-0.192	-0.274	0.756***	-0.300	-0.328
	(4.94)	(-0.34)	(-0.52)	(5.20)	(-0.48)	(-0.60)	(5.42)	(-0.54)	(-0.56)
β		0.522			0.827			1.108	
		(1.65)			(1.59)			(1.61)	
$\beta_{Downside}$			0.617*			0.956			1.188
			(1.69)			(1.63)			(1.63)
$R_{t-1.t-60}$	-0.198**	-0.057**	-0.001	-0.326**	-0.091**	-0.004	-0.387**	-0.132**	-0.030
	(-2.21)	(-2.16)	(-0.04)	(-2.03)	(-2.06)	(-0.17)	(-2.17)	(-2.31)	(-1.48)
Adj. R^2	0.231	0.443	0.456	0.239	0.415	0.429	0.230	0.406	0.418

[30] The results are available upon request.

From Table 11, the reversals are significantly larger under the rebalancing method; the lagged return coefficients are almost twice as large as compared to the buy-and-hold method (Table 7). The inclusion of traditional beta reduces the magnitude of the reversal coefficients, by nearly two-thirds, but it remains economically and statistically significant. From Table 11, the inclusion of traditional beta reduces the reversal coefficient from -0.39 (t-stat: -2.17) to -0.13 (t-stat: -2.31) for the five-year test period. As before, the inclusion of downside beta completely subsumes the reversal effect, as the respective coefficient is reduced to negligible levels [-0.03 (t-stat: -1.48)]. Thus, the relative explanatory power of traditional beta and downside beta are unchanged under the more "aggressive" method for computing future returns.

The vast majority of studies of long-horizon reversals use a sample of stocks listed on NYSE, as in our main analysis. The NYSE sample alleviates some concern regarding the sensitivity of contrarian returns to small firms [Fama and French (1988), Zarowin (1990)], stock price [Ball, et al(1995)], and the impact of the associated microstructure biases. But some studies include ASE or Nasdaq stocks [Lakonishok et al (1994), and Ball et al (1995) include securities listed on ASE]. Additionally, there is no consensus in the literature regarding the formation method and the size of the contrarian portfolios; Ball and Kothari (1989) and Chopra et al (1992) form 20 portfolios per estimation period, Lakonishok et al (1994) and Fama and French (1996) examine deciles, while other studies commit to portfolios with a fixed number of securities. These methodological choices might affect the magnitude of the reversal effect and inferences regarding the role of downside beta in explaining the phenomenon. In our main section, the choice of 20 portfolios is an attempt to balance the tradeoff involving the number of observations per period with the reduction in standard error of our risk estimates.

TABLE 12: Robustness Tests - Extended Sample/Number of Portfolios

The table presents Fama-MacBeth regressions of five-year test period returns on downside beta ($\beta_{Downside}$) and lagged five-year returns ($R_{t-1,t-60}$) for 10/20 portfolios per period and portfolios with a fixed number of securities (50), formed on the basis of their lagged returns. For portfolios with a fixed number of securities, any excess securities are assigned to the middle portfolio(s). The sample consists of all common stocks listed on NYSE, AMEX and NASDAQ. In Panel A future returns are calculated using the buy-and-hold method, while in Panel B the portfolios are rebalanced monthly. Cross-sectional regressions are estimated every year from 1931-2006 (76 test periods). Average coefficients and Newey-West corrected t-statistics (in parenthesis) are reported. Coefficients significant at the 10%, 5% and 1% level are denoted by (*), (**) and (***) respectively.

Panel A: Buy-and-Hold Method (Full Sample)

	10 portfolios per period			20 portfolios per period			Portfolios of 50 securities		
Intercept	0.752***	0.082	0.069	0.745***	0.169	0.134	0.739***	0.177	0.126
	(6.41)	(0.27)	(0.19)	(6.35)	(0.67)	(0.46)	(6.34)	(0.66)	(0.39)
β		0.701*			0.596*			0.581	
		(1.78)			(1.76)			(1.65)	
$\beta_{Downside}$			0.732			0.657*			0.655
			(1.64)			(1.75)			(1.59)
$R_{t-1,t-60}$	-0.259**	-0.101***	-0.045	-0.240**	-0.116***	-0.058***	-0.241**	-0.114***	-0.061*
	(-2.52)	(-3.30)	(-1.35)	(-2.55)	(-2.93)	(-2.69)	(-2.46)	(-2.93)	(-1.97)
Adj. R^2	0.336	0.541	0.563	0.263	0.428	0.438	0.218	0.363	0.376

Panel B: Rebalancing Method (Full Sample)

	10 portfolios per period			20 portfolios per period			Portfolios of 50 securities		
Intercept	0.828***	-0.745	-0.689	0.833***	-0.568	-0.556	0.819***	-0.617	-0.616
	(5.95)	(-1.19)	(-1.04)	(5.86)	(-1.02)	(-0.95)	(5.85)	(-1.03)	(-0.96)
β		1.665**			1.459**			1.526**	
		(2.16)			(2.13)			(2.05)	
$\beta_{Downside}$			1.649**			1.498**			1.568*
			(2.05)			(2.07)			(1.98)
$R_{t-1,t-60}$	-0.456**	-0.084***	0.040	-0.431**	-0.158***	-0.023	-0.439**	-0.090	0.026
	(-2.49)	(-2.92)	(0.83)	(-2.42)	(-2.82)	(-0.96)	(-2.32)	(-1.63)	(0.52)
Adj. R^2	0.320	0.549	0.577	0.256	0.453	0.468	0.224	0.397	0.412

Table 12 replicates our analysis of Table 7 for an extended sample that includes all securities listed on NYSE, ASE and Nasdaq for 10 and 20 portfolios per estimation period and for portfolios with a fixed number of securities (50). We also provide results for both the buy-and-hold and the rebalancing method. Comparing the central panels of Table 12 to our main results (Table 7), allows us to examine the effect of including securities listed on the other exchanges; reversals increase in magnitude, but the ability of traditional and downside beta to subsume the effect remains largely unchanged. The number of portfolios formed marginally affects the magnitude of reversals, but not inferences regarding the roles of traditional and downside risk in explaining reversals. To the contrary, our Table 7 finding that -- with the inclusion of downside beta the magnitude of the coefficient of past returns is substantially reduced but remains statistically significant (for the 5-year test period) -- appears to be the exception rather than the rule. In Table 12 downside beta subsumes the reversal coefficient completely in five out of the six specifications for the 5-year test period.[31]

Finally, in Table 13 we use the value-weighted index as a proxy for the market portfolio to place less emphasis on small capitalization stocks and the mean excess market return as an alternative threshold return for the estimation of downside beta. Again, our main results do not materially change.

[31] Downside beta also subsumes the past return coefficient for the shorter three and four year test periods (not shown in Table 12).

TABLE 13: Robustness Tests - Value-weighted index, Mean market return threshold

The table presents Fama-MacBeth regressions of test period returns (three to five years) on beta and downside beta estimated using the value-weighted CRSP index as the market proxy (β_{VW}, $\beta_{Downside\_VW}$), downside beta estimated using the mean market excess return as the threshold return ($\beta_{Downside\_mean}$) and lagged five-year returns ($R_{t-1,t-60}$) for 20 portfolios per period, formed on the basis of their lagged returns. The sample consists of all common stocks listed on NYSE. Cross-sectional regressions are estimated every year from 1931-2006 (76 test periods). Average coefficients and Newey-West corrected t-statistics (in parenthesis) are reported. Coefficients significant at the 10%, 5% and 1% level are denoted by (*), (**) and (***) respectively.

	Fut. 3-year Returns				**Fut. 4-year Returns**				**Fut. 5-year Returns**			
Intercept	0.401***	0.030	0.025	0.048	0.544***	0.041	0.050	0.088	0.706**	0.081	0.143	0.194
	(5.30)	(0.18)	(0.14)	(0.27)	(5.73)	(0.17)	(0.20)	(0.34)	(6.22)	(0.27)	(0.47)	(0.62)
β_{VW}		0.317*				0.431*				0.518*		
		(1.84)				(1.78)				(1.80)		
$\beta_{Downside\ VW}$			0.344*				0.459*				0.495	
			(1.79)				(1.71)				(1.62)	
$\beta_{Down\ mean}$				0.395				0.528				0.574
				(1.64)				(1.53)				(1.44)
$R_{t-1.t-60}$	-0.132**	-0.070**	-0.024	-0.017	-0.201**	-0.098**	-0.039**	-0.026*	-0.225**	-0.129***	-0.065**	-0.052**
	(-2.28)	(-2.46)	(-1.47)	(-1.17)	(-2.11)	(-2.36)	(-2.11)	(-1.91)	(-2.39)	(-2.66)	(-2.46)	(-2.25)
Adj. R^2	0.242	0.412	0.428	0.435	0.245	0.381	0.396	0.405	0.250	0.379	0.406	0.413

2.4 Conclusions

Our study provides compelling evidence that systematic downside risk can explain long-horizon return reversals. We show that from a downside risk perspective, losers are fundamentally riskier than winners, which can account for the observed future premia of contrarian portfolios. In doing so, we extend the intuition of Chan (1988) and Ball and Kothari (1989) -- that systematic risk can explain contrarian profits -- with a more efficient ex-ante risk measure that is not subject to the overconditiong problem or survivorship biases. Our empirical evidence suggests that downside risk explains the contrarian effect to a remarkable degree. Consistent with Fama and French (1996), our results suggest that distress risk plays an important role in reported contrarian profits. But that role is subsumed by the more general, more powerful, and more theoretically motivated measure -- downside risk. More broadly, our study adds to the growing body of evidence on the relevance of downside risk in asset pricing [Ang et al (2006)].

Bibliography

[1] Affleck-Graves John and Bill MacDonald, 1989, Nonnormalities and test of asset pricing theories, *Journal of Finance*, 44, 889-908.

[2] Amihud Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets*, 5, 31-56.

[3] Ang Andrew, Josheph Chen and Yuhang Xing, 2006, Downside risk, *Review of Financial Studies*, 19, 1191-1239.

[4] Arrow Kenneth J., 1964, The role of securities in the optimal allocation of risk, *Review of Economic Studies*, 31, 91-6.

[5] Artavanis Nikolaos T., 2012, On the Estimation of Systematic Downside Risk, Working paper.

[6] Artavanis Nikolaos T. and Gregory Kadlec, 2012, Downside risk and long-horizon stock return reversals, Working Paper.

[7] Ball Ray and S.P. Kothari, 1989, Non-stationary Expected Returns: Implications for Tests of Market Efficiency and Serial Correlation in Returns, *Journal of Financial Economics*, 25, 51-74.

[8] Ball Ray, S.P. Kothari and Jay Shanken, 1995, Problems in Measuring Portfolio Performance: An Application to Contrarian Investment Strategies, *Journal of Financial Economics*, 38, 79-107.

[9] Banz, R.W., 1981, The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9, 3-18.

[10] Barberis Nicholas and Ming Huang, 2008, The loss aversion/narrow framing approach to the equity premium puzzle, *Handbook of Equity Risk Premium*, 199-230.

[11] Barberis Nicholas, Ming Huang and Tano Santos, 2001, Prospect theory and asset prices, *Quarterly Journal of Economics*, 116, 1-53.

[12] Bawa Vijay and Eric B. Lindenberg, 1977, Capital market equilibrium in a mean-lower partial moment framework, *Journal of Financial Economics*, 5, 189-200.

[13] Baytas, Ahmet, and Nurset Cakici, 1999, Do Markets Overreact: International Evidence, *Journal of Banking and Finance*, 23, 1121–44.

[14] Black, Fischer, Michael C. Jensen, and Myron Scholes, 1972, The Capital Asset Pricing Model: Some empirical tests, Studies in the theory of capital markets.

[15] Blume, Marshall. 1970. "Portfolio Theory: A Step Towards Its Practical Application." *Journal of Business*, 43, 152-174.

[16] Blume, Marshall and Irwin Friend, 1973, A new look at the Capital Asset Pricing Model, *Journal of Finance*. 28, 19-33.

[17] Blume, Marshall E. and Robert F. Stambaugh, 1983, Biases in computed returns: An application to the size effect, *Journal of Financial Economics*, 12, 387-404.

[18] Boguth, Oliver, Murray Carlson, Adlai Fisher, and Mikhail Simutin, 2011, Conditional Risk and Performance Evaluation: Volatility Timing, Overconditioning, and New Estimates of Momentum Alphas, *Journal of Financial Economics*, 102, 363-389.

[19] Boynton Wentworth, and Henry R. Oppenheimer, 2006, Anomalies in stock market pricing: problems in return measurements, *Journal of Business*, 79, 2617-31.

[20] Campbell Y. John., Jens Hilscher and Jan Szilayi, 2008, In Search of Distress Risk, *Journal of Finance*, 63, 2899-2939.

[21] Chan K.C., 1988, On the Contrarian Investment Strategy, *Journal of Business*, 61, 147-63.

[22] Chan, K.C. and N. Chen, 1991, Structural and return characteristics of small and large firms, *Journal of Finance* 46, 1467-84.

[23] Chopra N., Lakonishok, J., and J. Ritter, 1992, Measuring abnormal performance: do stocks overreact, *Journal of Financial Economics*, 31, 235-268.

[24] Conrad Jennifer and Gautam Kaul, 1993, Long Term Market Overreaction or Biases in Computed Returns, *Journal of Finance*, 48, 39-63.

[25] De Bondt, Werner F. M., and Richard H. Thaler, 1985, Does the Stock Market Overreact?, *Journal of Finance*, 40, 793–805.

[26] De Bondt, Werner F. M., and Richard H. Thaler, 1987, Further Evidence on Investor Overreaction and Stock Market Seasonality, *Journal of Finance*, 42, 557–80.

[27] Debrew Gerard, 1959, Theory of Value, New York, Wiley.

[28] Dimson Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics*, 7,197-226.

[29] Dittmar, Robert F., 2002, Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns, *Journal of Finance,* 57, 369-403

[30] Estrada Javier, 2002, Systematic risk and emerging markets: The D-CAPM, *Emerging Markets Review*, 3, 365-79.

[31] Estrada Javier, 2004, The cost of equity of internet stocks: A downside risk approach, *European Journal of Finance*, 10, 239-54.

[32] Fama Eugene F., 1965, The behavior of stock market prices, *Journal of Business*, 38, 34-105.

[33] Fama Eugene F. and James D. MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy*, 81, 607-36.

[34] Fama Eugene F., and Kenneth French, 1992, The cross-section of expected stock returns, *Journal of Finance*, 47, 427-65.

[35] Fama Eugene F., and Kenneth French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics*, 33, 3-56.

[36] Fama Eugene F., and Kenneth French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55-84.

[37] Fama Eugene, and Kenneth French, 2008, Dissecting Anomalies, *Journal of Finance*, 63, 1653-78.

[38] Fishburn Peter C., 1977, Mean-risk analysis with risk associated with below-target returns, *American Economic Review*, 67, 116-26.

[39] Gerakos Joseph and Juhani T. Linnainmaa, 2012, The Unpriced Side of Value, Working Paper.

[40] Harlow, W. Van, and Ramesh K.S. Rao,1989, Asset pricing in a generalized mean-lower partial moment framework: theory and evidence, *Journal of Financial and Quantitative Analysis*, 24, 285-311.

[41] Harvey, Campbell, and Akhtar Siddique, 1999, Autoregressive conditional skewness, *Journal of Financial and Quantitative Analysis* 34, 465–87.

[42] Harvey, Campbell, and Akhtar Siddique, 2000, Conditional skewness in asset pricing model tests, *Journal of Finance,* 65,1263-95.

[43] Hogan William, and James Warren, 1974, Towards the development of an equilibrium capital-market model based on semi-variance, *Journal of Financial and Quantitative Analysis*, 9, 1-11.

[44] Jones Steven L., 1993, Another look at the time-varying risk and return in the long horizon contrarian strategy, *Journal of Financial Economics*, 33, 119-144.

[45] Jones, Steven L. and John C. Yeoman, 2012, Bias in estimating the systematic risk of extreme performers: implications for financial analysis, the leverage effect, and long-run reversals, *Journal of Corporate Finance*, 18, 1-21.

[46] Kahneman Daniel and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica*, 47, 263-91.

[47] Kapadia, Nishad, 2011, Tracking down distress risk, *Journal of Financial Economics*, 84, 358-88.

[48] Keim, Donald B., 1983, Size-related anomalies and stock return seasonality: Further empirical evidence, *Journal of Financial Economics*, 12, 13-32.

[49] Keim, Donald B., 1989, Trading patterns, bid-ask spreads and estimated security returns: The case of common stocks at calendar turning points, *Journal of Financial Economics*, 15, 75-98.

[50] Kraus, Alan, and Robert Litzenberger, 1976, Skewness preference and the valuation of risk assets, *Journal of Finance* 31, 1085–1100.

[51] Lakonishok Josef, Andrei Shleifer and Robert W.Vishny, 1994, Contrarian Investment, Extrapolation and Risk, *Journal of Finance*, 49, 1541-78.

[52] Lamont Owen, 2001. Economic tracking portfolios, *Journal of Econometrics*, 105, 161–184.

[53] Lo Andrew and Craig MacKinley, 1990, An econometric analysis of non-synchronous trading, *Journal of Econometrics*, 45, 181-211.

[54] Mao James C.T., 1970, Models of capital budgeting, E-V vs E-S, *Journal of Financial and Quantitative Analysis*, 4, 657-75.

[55] Markowitz, Harry, 1952, Portfolio selection, *Journal of Finance*, 7, 77-91.

[56] Markowitz, Harry, 1959, Portfolio selection. Efficient diversification of investments, John Wiley & Sons.

[57] Markowitz, Harry, 1991, Foundations of portfolio theory, *Journal of Finance*, 46, 469-77.

[58] Miller, Merton, and Myron Scholes, 1972, Rate of return in relation to risk: A reexamination of some recent findings, *Studies in the Theory of Capital Markets*, Michael C. Jensen, New York: Praeger, pp. 47-78.

[59] Moskowitz Tobias J., and Mark Grinblatt, 1999, Do Industries Explain Momentum?, *The Journal of Finance*, 54, 1249-90.

[60] Nantell Timothy J and Barbara Price, 1979, An analytical comparison of variance and semivariance capital market theories, *Journal of Financial and Quantitative Analysis*, 14, 221-242.

[61] Newey Whitney K. and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica*, 55, 703-8.

[62] Porter R.Burr, 1974, Semivariance and stochastic dominance: A comparison, *American Economic Review*, 64, 200-4.

[63] Post Thierry, Pim van Vliet and Simon Lansdorp, 2012, Sorting out downside beta, Working paper.

[64] Price Kelly, Barbara Price and Timothy J. Nantell, 1982, Variance and lower partial moment measures of systematic risk: Some analytical & empirical results, *Journal of Finance*, 37, 843-55.

[65] Reinganum, M.R., 1981. Misspecification of asset pricing: Empirical anomalies based on earnings' yields and market values. Journal of Financial Economics 9, 19-46.

[66] Richards Antony J., 1997, Winner-Loser Reversals in National Stock Market Indices: Can They be Explained?, *Journal of Finance*, 52, 2129-44.

[67] Richardson Matthew and Tom Smith, 1993, A test of multivariate normality in stock returns, *Journal of Business*, 66, 295-321.

[68] Roy A.D., 1952, Safety first and the holding of assets, *Econometrica,* 20, 431-49.

[69] Scholes Myron, and Williams Joseph, 1977, Estimating betas from nonsynchronous data, *Journal of Financial Economics*, 5, 309-327.

[70] Smith, Daniel R., 2007, Conditional coskewness and asset pricing, *Journal of Empirical Finance*, 14(1), 91-119.

[71] Vassalou, M., and Y. Xing, 2004, Default Risk in Equity Returns, *Journal of Finance*, 59, 831-868.

[72] Zarowin Paul, 1990, Size, Seasonality and Stock Market Overreaction, *Journal of Financial and Quantitative Analysis*, 25, 113-25.

Appendix

TABLE A1: Fama-MacBeth Regressions (10 and 30 Portfolios per Period)

The table presents the results of Fama-MacBeth regressions of one-year test period returns on beta (β) and downside beta (β_{HW}^{-}). The analysis refers to 10 (Panel A) and 30 portfolios (Panel B) per period, formed on the basis of the unconditional beta of the securities over the 5-year (formation) period preceding the estimation period (Panel B). Cross-sectional regressions are estimated every year from 1936-2010, yielding 75 formation/estimation/test periods. Average coefficients and Newey-West corrected t-statistics (in parenthesis) are reported. The Adjusted-R^2 is reported in the last row of each panel. Coefficients significant at the 10%, 5% and 1% level are denoted by (*), (**) and (***) respectively.

	Unconditional vs Downside Beta					
	10 Beta-sorted Portfolios			**30 Beta-sorted Portfolios**		
Intercept	0.044*	0.030	0.051*	0.050**	0.036	0.037
	(1.71)	(1.11)	(1.93)	(2.02)	(1.40)	(1.49)
$\boldsymbol{\beta}$	**0.083****		-0.041	**0.076****		-0.075
	(2.52)		(-0.40)	(2.40)		(-1.55)
$\boldsymbol{\beta_{HW}^{-}}$		**0.099*****	0.117		**0.093****	**0.167*****
		(2.70)	(1.27)		(2.61)	(3.34)
Adj. $\boldsymbol{R^2}$	0.487	0.477	0.496	0.329	0.327	0.344
	Number of periods: 75, Number of observations: 750			*Number of periods: 75, Number of observations: 2250*		