A New Formula for the Expected Excess Return of the Market

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Abstract

Key to deriving the lower bound to the expected excess return of the market in Martin (2017) is the assumption of the negative correlation condition (NCC). We improve on the lower bound characterization by proposing an exact formula for the conditional expected excess return of the market. In our formula, each risk-neutral return central moment contributes to the expected excess return and is representable in terms of known option prices. To interpret theoretical and empirical distinctions between our formula and the lower bound, we develop and study the asset-pricing restrictions of the NCC.

Keywords: Expected excess return of the market, negative correlation condition, lower bound

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I still remember the teasing we financial economists, Harry Markowitz, William Sharpe, and I, had to put up with from the physicists and chemists in Stockholm when we conceded that the basic unit of our research, the expected rate of return, was not actually observable. — Merton Miller. The History of Finance, Journal of Portfolio Management 1999 (Summer), 95–101.

1 The negative correlation condition in Martin (2017)

We employ the following notation:

\[ S_{t+T} = \text{price of the equity market index at some future date } t + T; \]
\[ R_T \equiv \frac{S_{t+T}}{S_t} = \text{gross return of the equity market index over } t \text{ to } t + T. \text{ Assume } R_T > 0; \]
\[ E_t^P(.) = \text{expectation under the real-world probability measure, } P; \]
\[ E_t^Q(.) = \text{expectation under the risk-neutral probability measure, } Q; \]
\[ M_T = \text{stochastic discount factor, with } E_t^P(M_T R_T) = 1 \text{ holding; } \]
\[ R_{f,t} = \frac{1}{E_t^P(M_T)} = E_t^Q(R_T) = T-\text{period gross risk-free return; } \]
\[ 1 = \text{conformable vector of ones; } \]
\[ Z_T[R_T] = \text{gross return vector contingent on } R_T \text{ and satisfies } E_t^P(M_T Z_T[R_T]) = 1; \]
\[ M_T[R_T] = \text{projected stochastic discount factor, with } E_t^P(M_T[R_T] Z_T[R_T]) = 1 \text{ holding; } \]
\[ \text{call}_{t,T}[K] = \text{time } t \text{ price of the call option on the market, with strike } K, \text{ expiring in } T-\text{periods; } \]
\[ \text{put}_{t,T}[K] = \text{time } t \text{ price of the put option on the market, with strike } K, \text{ expiring in } T-\text{periods; } \]
\[ \text{cov}_t^P(\tilde{x}, \tilde{y}) = \text{conditional covariance between two random variables } \tilde{x} \text{ and } \tilde{y} \text{ under } P; \]
\[ \text{var}_t^Q(R_T) = \text{conditional variance of } R_T \text{ under the risk-neutral measure } Q. \]

**Definition 1** *(Negative correlation condition, NCC):* The NCC is the assumption that
\[ \text{cov}_t^P(M_T R_T, R_T) \leq 0, \text{ for all } M_T \text{ satisfying } E_t^P(M_T R_T) = 1. \]
Martin (2017) introduces the relation in equation (1) and derives the conditional lower bound, 
\( R_{f,t}^{-1} \text{var}^Q_t (R_T) \), of the expected excess return of the market, as follows:

\[
\mathbb{E}_t^P (R_T) - R_{f,t} = \mathbb{E}_t^P (M_T) \left( \frac{M_T}{\mathbb{E}_t^P (M_T)} R_T^2 - \frac{1}{\mathbb{E}_t^P (M_T)^2} \right) - \text{cov}_t^P (M_T R_T, R_T)
\]

\[
\geq R_{f,t}^{-1} \text{var}^Q_t (R_T) \quad \text{(provided the NCC holds)}
\]

The lower bound of the expected excess return of the market can be inferred from option prices as
\[
\frac{2}{S_t^2} \int_{K<R_{f,t}S_t} \text{put}_{t,T}[K] dK + \frac{2}{S_t^2} \int_{K>R_{f,t}S_t} \text{call}_{t,T}[K] dK.
\]

The lower bound in equation (2) touches a theme dating back to Merton (1980), Black (1993), and Elton (1999) on how elusive it is to estimate the expected return of the market. The topic is cutting-edge, and peer-reviewed academic evidence on the lower bound of the expected excess return remains relevant and influential, and is invigorating research complementarities in theory and practice (see, e.g., Chabi-Yo and Loudis (2019), Kadan and Tang (2019), Martin and Wagner (2019), and Schneider and Trojan (2019), among others).

Improving on the lower bound characterization in Martin (2017), our innovation is an exact theoretical representation for \( \mathbb{E}_t^P (R_T) - R_{f,t} \), which can be synthesized from quantities inferred from option prices, specifically, the risk-neutral return central moments of order higher than one.

The big picture question is: How should one view our expression for \( \mathbb{E}_t^P (R_T) - R_{f,t} \) in light of the lower bound formula? We show empirically that there are sizable differences between our estimates of \( \mathbb{E}_t^P (R_T) - R_{f,t} \) versus those from Martin (2017). Our steps to synthesizing \( \mathbb{E}_t^P (R_T) - R_{f,t} \) from option prices do not utilize the formalism of the NCC (i.e., whether \( \text{cov}_t^P (M_T R_T, R_T) \leq 0 \)).

The following features further guide our theoretical and empirical investigation. First, the inequality in equation (2) holds under all change-of-measure densities (i.e., for every \( M_T \)) such that \(-\text{cov}_t^P (M_T R_T, R_T)\) is nonnegative for each \( t \). Second, the derived lower bound in equation (2) is theoretically unsupportable if one could find an economically plausible \( M_T \) for which \( \text{cov}_t^P (M_T R_T, R_T) \) is positive. If the NCC is not a generic property at each date \( t \), then having analytical formulations of \( \mathbb{E}_t^P (R_T) - R_{f,t} \) are of value. Addressing this issue, we identify the theoretical asset-pricing restrictions that underlie the NCC, and then propose empirical tests. We show that if \( \text{cov}_t^P (M_T R_T, R_T) > 0 \), then \( R_{f,t}^{-1} \text{var}^Q_t (R_T) \) is an upper bound and not a lower bound.
We assume that there exists a projected SDF, $M_T[R_T]$, in the sense of Rosenberg and Engle (2002, Section 2.2), satisfying $M_T[R_T] > 0$, $\mathbb{E}^P_t(M_T[R_T]) = \frac{1}{R_{f,t}} < \infty$, $\mathbb{E}^P_t(M_T[R_T] R_T) = 1$, and $\mathbb{E}^P_t(\{M_T[R_T]\}^2) < \infty$.

Why focus on SDFs that are a function of $R_T$? For one, Martin (2017) posits that if $M_T = \frac{1}{R_T}$, then $\text{cov}^P_t(M_T R_T, R_T) = 0$, and $R_{f,t}^{-1} \text{var}^Q_t(R_T)$ is the tightest lower bound for $\mathbb{E}^P_t(R_T) - R_{f,t}$ and can be extracted from option prices on the market index. For another, as shown in Rosenberg and Engle (2002), when it comes to considering claims written on the market return for which data can be exploited, it suffices to work with the projection of the SDF (even though the SDF itself may admit additional state dependencies) onto the space generated by the market return. Thus, we need only model $\mathbb{E}^P_t(\mathcal{M} | R_T)$, for any $\mathcal{M}$ that represents the change of probability with the bond price as numeraire, without the necessity of exploring state-dependent specifications of the SDF (e.g., Campbell and Cochrane (1999), Epstein and Zin (1991), and Hansen and Renault (2009)).

Informed by theory and data from options markets, our novelty is to develop a theoretical representation for $\mathbb{E}^P_t(R_T) - R_{f,t}$, which can be compared with Martin (2017). Our characterization of $\mathbb{E}^P_t(R_T) - R_{f,t}$ is consistent with asset-pricing theory, does not require exploiting the workings of the NCC (i.e., $\text{cov}^P_t(M_T R_T, R_T) \leq 0$), and can be employed in empirical applications.

**Result 1 (Expected excess return of the market)** Suppose $M_T$ is of the following form:

$$M_T[R_T] = \exp (m_0 - 1 - \phi (R_T - R_{f,t})), \quad \text{for some constants } m_0 \text{ and } \phi > 0. \quad (3)$$

Then, the conditional expected excess return of the market can be decomposed, as follows:

$$\mathbb{E}^P_t(R_T) - R_{f,t} = \frac{1}{\phi} \left( \{\phi \text{SD}^Q_t(R_T)\}^2 + \frac{1}{2} \{\phi \text{SD}^Q_t(R_T)\}^3 \times \text{Skewness}^Q_t(R_T) + \frac{1}{6} \{\phi \text{SD}^Q_t(R_T)\}^4 \times \{\text{Kurtosis}^Q_t(R_T) - 3\} + \frac{1}{24} \{\phi \text{SD}^Q_t(R_T)\}^5 \{\text{Hskewness}^Q_t(R_T) - 10 \text{Skewness}^Q_t(R_T)\} + \ldots \right), \quad (4)$$

where $\text{SD}^Q_t(R_T) \equiv \sqrt{\text{var}^Q_t(R_T)}$, $\text{Skewness}^Q_t(R_T)$, $\text{Kurtosis}^Q_t(R_T)$, $\text{Hskewness}^Q_t(R_T) \equiv \frac{\text{Skewness}^Q_t(R_T)}{\{\text{SD}^Q_t(R_T)\}^5}$ are, respectively, the conditional risk-neutral return volatility, skewness, kurtosis, and hyperskew-
ness. Each risk-neutral return central moment is algebraic in option prices (as displayed in equations (A36)–(A39) of Appendix A).

**Proof:** See Appendix A. ■

The formula in equation (4) deduces a value for $E_P^t(R_T) - R_{f,t}$ and not just a lower bound. This new estimate of $E_P^t(R_T) - R_{f,t}$, at each date $t$, is expressed as an infinite series, with each term related to risk-neutral return central moments of order higher than one. However, successively smaller weights are assigned to Skewness$^Q_t(R_T)$, to $\{Kurtosis^Q_t(R_T) - 3\}$, and to $\{Hskewness^Q_t(R_T) - 10Skewness^Q_t(R_T)\}$, provided that the $T$ period $SD^Q_t(R_T)$ satisfies $\{\phi SD^Q_t(R_T)\} < 1$.

Our approach is to consider the $P$-measure return density as a weighted $Q$-measure return density, as warranted by the form of $M_T$ in equation (3). Then, we exploit the properties of the cumulant generating functions under $P$ and $Q$ (as detailed in Appendix A). Crucially, no parametric assumptions are made about the risk-neutral density of market returns.

Furthermore, equation (4) does not specialize to the tightest lower bound in Martin (2017) (i.e., $R_{f,t}^{-1} (SD^Q_t(R_T))^2$), as the specification $M_T = 1/R_T$ is not subsumed within equation (3).

The form of $M_T$ in equation (3) is an assumption about the projected SDF and is complementary to Schneider and Trojani (2019). They, in essence, project the SDF onto $(R_T, R_T^2, R_T^3, \ldots)$. Taking a Taylor series of $M_T[R_T]$ in equation (3), one obtains $M_T[R_T] = e^{m_0 - 1} \left(1 + \phi(R_T - R_{f,t})\right) + \frac{1}{2} \left(-\phi(R_T - R_{f,t})\right)^2 + \frac{1}{6} \left(-\phi(R_T - R_{f,t})\right)^3 + \frac{1}{24} \left(-\phi(R_T - R_{f,t})\right)^4 + \ldots$, and, so, intuitively speaking, our equation (3) involves an infinite series of polynomials and is akin to Rosenberg and Engle (2002, equation (12)).

Our analytical representation of $E_P^t(R_T) - R_{f,t}$ is a step forward, as Schneider and Trojani (2019) use assumptions about the sign of the covariance, under $P$, between the SDF and various moments of the market return to obtain bounds on the $P$ moments of the market return.

Our $M_T$ in equation (3) is economically motivated, is informed by the data, and can arise in the context of minimum discrepancy problems considered in Borovička, Hansen, and Scheinkman (2016, Section VIII.B), Almeida and Garcia (2017), and Ghosh, Julliard, and Taylor (2017). Specifically, one solves $\inf_{M \in M} E_P^P(M \log M)$ with $M \equiv \{M > 0$ such that $E_P^P(M(R - R_f)) = 0$, $E_P^P(M) = E_P^P(R_{f,t}^{-1}) \equiv \mu_M$, and $E_P^P(M \log M) < \infty\}$, where $E_P^P(\cdot)$ is unconditional expectation. The solution
is \( M^* = \exp(m_0^* - 1 - \phi^*(R - R_f)) \), where \((\phi^*, m_0^*)\) solve \( \arg \inf_{(\phi, m_0)} \{-m_0 \mu + \mathbb{E}_T^P(\exp(m_0 - 1 - \phi(R - R_f)))\} \). The essence of the estimation procedure is that \( M_T \), parameterized by \( \phi \), enforces the correct unconditional pricing of the excess return of the market.

Our implementation indicates that the estimate of \( \phi \) is 2.274, with a 90\% bootstrap confidence interval of (1.30 3.29). See the note to Table 1. In our setup, \( \phi \) reflects the sensitivity \( \frac{d \log M_T[R_T]}{d R_T} \).

Furthermore, \( \mathbb{E}_t^P(R_T) - R_{f,t} \) is unaffected by \( m_0 \).

What is the value-added of our formula? It mitigates theoretical and empirical reliance on the NCC and on the conditional lower bound on the expected excess return of the market.

The first question we ask is the following: How reasonable are our estimates of \( \mathbb{E}_t^P(R_T) - R_{f,t} \)? To answer this, we use monthly return data covering 348 nonoverlapping option expiration cycles (\( T=28 \) days) on the S&P 500 equity index, from January 1990 to December 2018 (29 years). Following convention, we retain all options with prices up to the minimum tick size. Table 1 presents features of our estimates of \( \mathbb{E}_t^P(R_T) - R_{f,t} \).

The annualized average expected excess return is 8.97\% (median is 5.8\%) over the 29-year sample. There is considerable time variation, as depicted in Figure 1, with a 5th (95th) percentile value of 1.8\% (26.2\%). Our average \( \mathbb{E}_t^P(R_T) - R_{f,t} \) of 8.97\% can be compared to the very long-run average market excess return of 7.81\% over 1926:07–2018:12. Furthermore, it is comparable to the estimate of 7.43\% reported in Fama and French (2002) over 1951–2000. Fundamental to our methodology is the development of a portfolio of risk-neutral return central moments that synthesizes the conditional expected excess return of the market.

The next pertinent question is the following: How aligned is the lower bound, \( R_{f,t}^{-1} \text{var}_t^Q(R_T) \), with our estimates of \( \mathbb{E}_t^P(R_T) - R_{f,t} \)? We perform the following regression:

\[
\frac{\mathbb{E}_t^P(R_T) - R_{f,t}}{\text{estimated from equation (4)}} = \Psi_0 + \Psi_1 \left\{ R_{f,t}^{-1} \text{var}_t^Q(R_T) \right\} + \tilde{\epsilon}_t, \tag{5}
\]

with hypothesis of \( \Psi_0 = 0 \) and \( \Psi_1 = 1 \).

To compute \( p \)-values, we rely on the HAC estimator of Newey and West (1987), with automatically selected lags. The Wald test of \( \Psi_0 = 0 \) and \( \Psi_1 = 1 \), which reflects \( \text{cov}_t^P(M_T R_T, R_T) = 0 \), is rejected with a \( p \)-value of 0.00. We obtain \( \Psi_0 = 0.35 \) (\( p \)-value of 0.00) and \( \Psi_1 = 1.99 \) (\( p \)-value of 0.00).
In Martin (2017, Table 1), the average lower bound, $R_{f,t}^{-1} \text{var}_t^Q(R_T)$, is 5\% over the sample of 1/1996 to 1/2012. Our Table 1 (row (vi)) shows that the average $R_{f,t}^{-1} \text{var}_t^Q(R_T)$ is 4.32\%, and is half the size of the average $E_t^P(R_T) - R_{f,t}$. The difference $\{E_t^P(R_T) - R_{f,t}\} - R_{f,t}^{-1} \text{var}_t^Q(R_T) = -\text{cov}_t^P(M_T R_T, R_T)$, as plotted in Figure 2, manifests substantial dispersion through time.

Prompted by Barro (2006) and Wachter (2013), we investigate two additional questions using our method to estimate $E_t^P(R_T) - R_{f,t}$.

How important is the perception of return extremes for $E_t^P(R_T) - R_{f,t}$? We find empirically that the contribution of $\frac{1}{2\sqrt{\phi}} \{\phi SD_t^Q(R_T)\}^5 \{\text{Hskewness}_t^Q(R_T) - 10 \text{Skewness}_t^Q(R_T)\}$ to $E_t^P(R_T) - R_{f,t}$ is 0.006\% annualized (on average; see row (v) of Table 1). Additionally, Table 1 (row (ii)) reveals that the average $\frac{1}{\phi} \{\phi SD_t^Q(R_T)\}^2 + \frac{1}{2} \{\phi SD_t^Q(R_T)\}^3 \times \text{Skewness}_t^Q(R_T)$ is 8.91\%, implying an average contribution of $\frac{1}{\phi} \{\phi SD_t^Q(R_T)\}^4 \times \{\text{Kurtosis}_t^Q(R_T) - 3\}$ of 0.049\% (see row (iv)). Our estimates indicate that tail effects matter little quantitatively, on average.

How important is the perception of disasters, as reflected in the relative pricing of OTM puts versus OTM calls, for $E_t^P(R_T) - R_{f,t}$? To answer this, we compute the average of $\frac{1}{2\sqrt{\phi}} \{\phi SD_t^Q(R_T)\}^2$ and obtain a value of 9.84\%. See Table 1 (row (iii)). Thus, the presence of $\frac{1}{2} \{\phi SD_t^Q(R_T)\}^3 \times \text{Skewness}_t^Q(R_T)$ reduces the conditional expected excess return of the market, on average, by −0.93\% (the estimate of risk-neutral skewness is never positive). Hence, there is information for expected excess returns in the risk-neutral third central moment.

What are the other implications of formula (4) and Table 1? The cornerstone of Martin and Wagner (2019) is the expression for $E_t^P(R_t^J) - E_t^P(R_T)$ (their equation (14)), for individual stocks $j = 1, \ldots, J$, and for the expected excess return of an individual stock $E_t^P(R_t^j) - R_{f,t}$ (their equation (15)). The former expression does not depend upon the validity of the NCC, but the latter requires an estimate (and not only a lower bound) of the expected return of the market. To obtain this estimate, an assumption is made that $\text{cov}_t^P(M_T R_T, R_T)$ is identically zero. Thus, given the documented disparities between $\{E_t^P(R_T) - R_{f,t}\} - R_{f,t}^{-1} \text{var}_t^Q(R_T)$, a central input to $E_t^P(R_t^J) - R_{f,t}$ is susceptible to misspecification. Our estimates of $E_t^P(R_T)$ and $-\text{cov}_t^P(M_T R_T, R_T) = \{E_t^P(R_T) - R_{f,t}\} - R_{f,t}^{-1} \text{var}_t^Q(R_T)$, using formula (4), can improve implementational aspects in Martin and Wagner (2019).
Chabi-Yo and Loudis (2019, equations (27) and (31)) present a lower bound on \( \mathbb{E}_t^P(R_T) - R_{f,t} \), derived from risk-neutral return variance, skewness, and kurtosis. Our departure in equation (4) is that it offers an explicit expression for the conditional expected excess return of the market.

Finally, what could be the reasons that the lower bound (i.e., \( R^{-1}_{f,t} \text{var}_t^Q(R_T) \)) is not adequately aligned with our estimates of \( \mathbb{E}_t^P(R_T) - R_{f,t} \)? First, informed by theory, our formula unpacks the contribution of other risk-neutral return central moments. Second, if the NCC were not to be a generic property, what, at first sight, appears to be the lower bound, could, in fact, be an upper bound. We develop this formally in Result 3. Hence, knowledge of the lower bound on the expected excess return of the market is of limited value if the NCC were to be violated.

3 A general formula for the expected excess return of the market

The specification of \( M_T \) in equation (3), which is an exponential function of \( R_T \), balances tractability and generality. The projected SDF is analytic (i.e., \( M_T \in \mathcal{C}^\infty \)) and can be viewed as a polynomial in \( R_T \) through its Taylor expansion.

One may inquire: Can one generalize the functional form for \( M_T \) for which one could obtain analytical expressions for \( \mathbb{E}_t^P(R_T) - R_{f,t} \), and still use input variables constructed from option prices?

To explore this possibility, we maintain that \( M_T[R_T] > 0 \) almost surely, and \( M_T[R_T] \), or equivalently, \( M_T[1 + r_T] \) (recalling \( r_T \equiv R_T - 1 \) and \( r_{f,t} \equiv R_{f,t} - 1 \)), is continuous and infinitely differentiable in \( r_T \), that is, \( M_T[1 + r_T] \in \mathcal{C}^\infty \). We define

\[
H[r_T] = \frac{1}{M_T[R_T]} = \frac{1}{M_T[1 + r_T]} \in \mathcal{C}^\infty.
\]  

This class may encompass theoretically plausible and empirically interesting specifications of projected SDFs, allowing us to comment on the robustness of our estimates of \( \mathbb{E}_t^P(R_T) - R_{f,t} \) in Table 1. Additionally, no assumptions are made about whether the NCC holds.
Denoting $H'[r_T] \equiv \frac{dH[r_T]}{dr_T}$, $H''[r_T] \equiv \frac{d^2H[r_T]}{dr_T^2}$, $H'''[r_T] \equiv \frac{d^3H[r_T]}{dr_T^3}$, and $H''''[r_T] \equiv \frac{d^4H[r_T]}{dr_T^4}$, and $H[r_{f,t}] = H[r_T]|_{r_T=r_{f,t}}$, $H'[r_{f,t}] = H'[r_T]|_{r_T=r_{f,t}}$ and so on, we consider the Taylor expansion

$$H[r_T] = H[r_{f,t}] + H'[r_{f,t}](r_T - r_{f,t}) + \frac{H''[r_{f,t}]}{2}(r_T - r_{f,t})^2$$
$$+ \frac{H'''[r_{f,t}]}{3!}(r_T - r_{f,t})^3 + \frac{H''''[r_{f,t}]}{4!}(r_T - r_{f,t})^4 + \cdots. \quad (8)$$

We assume that $\frac{H'[r_{f,t}]}{H[r_{f,t}]}$, $\frac{H''[r_{f,t}]}{H[r_{f,t}]}$, $\frac{H'''[r_{f,t}]}{H[r_{f,t}]}$, and $\frac{H''''[r_{f,t}]}{H[r_{f,t}]}$ exist and are well-defined.

**Result 2 (Expected excess return of the market when $H[r_T] \in C^\infty$)** With the function $H[r_T]$ defined in equation (7), the conditional expected excess return of the market is

$$E^T_T (R_T) - R_{f,t} = \frac{H'[r_{f,t}]}{H[r_{f,t}]} \{SD^T_T (R_T)\}^2 + \frac{1}{2} \frac{H''[r_{f,t}]}{H[r_{f,t}]} \{SD^T_T (R_T)\}^3 \times \text{Skewness}^T_T (R_T)$$
$$+ \frac{1}{6} \frac{H'''[r_{f,t}]}{H[r_{f,t}]} \{SD^T_T (R_T)\}^4 \times \{\text{Kurtosis}^T_T (R_T) - 3\} + \cdots. \quad (9)$$

**Proof:** See Appendix B. ■

When $M_T$ is specialized to $\exp (m_0 - 1 + \phi (r_T - r_{f,t}))$ (as in equation (3)), then $H[r_T] = \exp (-m_0 + 1 + \phi (r_T - r_{f,t}))$. Hence, $\frac{H'[r_{f,t}]}{H[r_{f,t}]} = \phi$, $\frac{H''[r_{f,t}]}{H[r_{f,t}]} = \phi^2$, and $\frac{H'''[r_{f,t}]}{H[r_{f,t}]} = \phi^3$. In this case, equation (9) coincides with the exact expression for $E^T_T (R_T) - R_{f,t}$ in equation (4). Our motivation for featuring $M_T$ in equation (3) was twofold. First, to show that risk-neutral return central moments higher than two are important for $E^T_T (R_T) - R_{f,t}$. This effort was guided by the bounds formula of Martin (2017), whose sole driver is the risk-neutral return variance. Second, to offer a parsimonious, easy to implement formula in which the unknown parameter could be estimated using established methods.

Result 2 inherits the convenience of Result 1, but enhances flexibility and generality. For one, it can allow for state-dependent sensitivity of $M_T$ to $R_T$. For another, it can accommodate alternative forms of dependencies of $M_T$ on $R_T$. The following parameterizations illustrate our points and may offer potential avenues for improvement.

**Case 1 (State-dependent sensitivity)** Suppose $M_T$ is of the following form:

$$M_T [R_T] = \exp (m_0 - 1 - \{\phi + \phi_2 z_t\} (R_T - R_{f,t})), \quad \text{for constants } m_0, \phi > 0, \text{and } \phi_2, \quad (10)$$
where \( z_t \) is some economically relevant variable known at time \( t \) (e.g., changes in variance uncertainty). We deduce that \( \mathbb{E}_t^P(R_T) - R_{f,t} \) satisfies equation (9), with

\[
\frac{H'[r_{f,t}]}{H[r_{f,t}]} = \phi + \phi_z z_t, \quad \frac{H''[r_{f,t}]}{H[r_{f,t}]} = (\phi + \phi_z z_t)^2, \quad \text{and} \quad \frac{H'''[r_{f,t}]}{H[r_{f,t}]} = (\phi + \phi_z z_t)^3. \tag{11}
\]

**Case 2 (Alternative form of dependencies)**

Suppose

\[
M_T[R_T] = \exp \left( m_0 - 1 - \phi (R_T - R_{f,t}) + \psi \left( \frac{\log(R_T)}{\varphi_t} - R_{f,t} \right) \right), \tag{12}
\]

where \( \varphi_t \equiv \frac{1}{R_{f,t}} \mathbb{E}_t^Q(\log(R_T)) = 1 - \frac{1}{R_{f,t}} + \int_{K<S_t} \Gamma_{put,t,T}[K] dK + \int_{K>S_t} \Gamma_{call,t,T}[K] dK \) is the price of the log\((R_T)\) payoff. We deduce that \( \mathbb{E}_t^P(R_T) - R_{f,t} \) satisfies equation (9), with

\[
\frac{H'[r_{f,t}]}{H[r_{f,t}]} = \phi - \frac{\psi}{\varphi_t R_{f,t}}, \tag{13}
\]

\[
\frac{H''[r_{f,t}]}{H[r_{f,t}]} = \frac{\varphi_t^2 (R_{f,t})^2 \phi^2 + \varphi_t \{ \psi - 2 R_{f,t} \psi \phi \} + \psi^2}{\varphi_t^2 (R_{f,t})^2}, \tag{14}
\]

\[
\frac{H'''[r_{f,t}]}{H[r_{f,t}]} = \frac{\varphi_t^3 (R_{f,t})^3 \phi^3 - 3 \varphi_t^2 \psi (3(R_{f,t})^2 \phi^2 - 3 R_{f,t} \phi + 2) + 3 \varphi_t \psi^2 (R_{f,t} \phi - 1) - \psi^3}{\varphi_t^3 (R_{f,t})^3}. \tag{15}
\]

What are the defining features of these formulae? In each case, \( \mathbb{E}_t^P(R_T) - R_{f,t} \) depends on all risk-neutral return central moments, and not just on the risk-neutral variance. Second, the sensitivity of \( \mathbb{E}_t^P(R_T) - R_{f,t} \) to each risk-neutral central moment is time-varying.

Case 2 admits a general form of dependencies since \( \log(1+r_T) = r_T - \frac{r_T^2}{2} + \frac{r_T^3}{3} - \frac{r_T^4}{4} + \frac{r_T^5}{5} \ldots \), and hence \( \log M_T \) is a polynomial in the net market return \( r_T \), with state-dependent (via \( \varphi_t \)) parameterized sensitivities. While such generalizations are implementable, they appear more cumbersome.

Framing our issues in the context of Case 1 and equation (10), Table 2 reports the results when we take a stand on the choice of \( z_t \). The question is whether the data supports time-varying sensitivity, \( \phi + \phi_z z_t \), of \( M_T \) to \( R_T \), which is equivalent to testing whether \( \phi_z = 0 \). Our estimation procedure is analogous to that used for equation (3), except that \( M_T \) is parameterized by \( \phi \) and \( \phi_z \) (for a choice of \( z_t \)). See the note to Table 2.

Guided by empirical and theoretical considerations (e.g., see, among others, Cochrane (1996) and Menzly, Santos, and Veronesi (2004)), we consider \( z_t \) to be the change in prior month realized
market variance or the prior one month return on the HML factor. The HML factor is often associated with variation in business conditions (e.g., Fama and French (1993)). The framework of Case 1 accommodates the use of economically relevant $z_t$ variables amenable to construction over option expiration cycles.

There are two takeaways from Table 2. First, the 90% confidence intervals of both $\phi_z$ estimates bracket zero, implying that the data does not support a time-varying effect of $R_T$ on $M_T$ beyond that reflected in $\phi$ (for our considered choices of $z_t$). Second, the estimates of $E^p_t(R_T) - R_{f,t}$, using equation (10), align with those in Table 1. Thus, the parsimoniously specified $M_T$ in equation (3) may be preferred over the more complicated counterparts.

4 Developing and testing the asset-pricing restrictions of the NCC

The theoretical lower bound (i.e., $R_{f,t}^{-1} \var^Q_t(R_T)$) — which is a consequence of the NCC — is the estimate of the conditional expected excess return of the market. This section develops and identifies theoretical restrictions on $M_T$ to ascertain the generality of the NCC. The empirical evidence on testing the NCC helps to reconcile our perspective on considering exact theoretical representations of $E^p_t(R_T) - R_{f,t}$. Additionally, we construct theoretical (but empirically plausible) economies in which the NCC fails to hold.

4.1 Theoretical restrictions of the NCC

We first present a theoretical result that gives a sufficient condition on the sign of the conditional covariance between a random variable $X$ and a function $g[X]$ (suppressing subscript $T$ on $X_T$).

Lemma 1 (Sign of conditional covariance) Let $X$ be a random variable with a finite second moment, $\mathcal{D}$ be a subset of the real line $\mathbb{R}$ with $E^p_t(X) \in \mathcal{D}$, and $g : \mathcal{D} \to \mathbb{R}$ be a function for which $g[X]$ has a finite second moment. The following statements are true:

\begin{align}
\text{If } g[X] \text{ is a decreasing function on } \mathcal{D}, \text{ then } \text{cov}^p_t(g[X], X) & \leq 0. \\
\text{If } g[X] \text{ is an increasing function on } \mathcal{D}, \text{ then } \text{cov}^p_t(g[X], X) & \geq 0.
\end{align}

Proof: See Appendix C.
The essence of Lemma 1 is that if $\frac{dg(X)}{dX} = g'(X) \geq 0$, then $g[X]$ is decreasing (increasing), so Lemma 1 tells us that the conditional covariance $\text{cov}_i^\mathcal{P}(g[X], X)$ is nonpositive (nonnegative).

In view of Lemma 1, what are the theoretical restrictions on plausible $M_T$ under which the NCC does not hold? We answer this question by developing a result on the sign of $\text{cov}_i^\mathcal{P}(M_T[R_T], R^n_T)$ for any positive integer $n$ and then specializing the result to $n = 1$. Let $M'_T[R_T] = \frac{dM_T[R_T]}{dR_T}$.

**Result 3 (Restrictions of the NCC)** The following hold for any positive integer $n$:

If $\frac{M'_T[R_T]}{M_T[R_T]} + \frac{n}{R_T} \leq 0$ almost surely, then $\text{cov}_i^\mathcal{P}(M_T[R_T], R^n_T) \leq 0$.

If $\frac{M'_T[R_T]}{M_T[R_T]} + \frac{n}{R_T} \geq 0$ almost surely, then $\text{cov}_i^\mathcal{P}(M_T[R_T], R^n_T) \geq 0$.

Furthermore,

If $\frac{M'_T[R_T]}{M_T[R_T]} + \frac{n}{R_T} \leq 0$, then $\mathbb{E}_i^\mathcal{P}(R^n_T) \geq \frac{\mathbb{E}_i^Q(R^n_T) - \mathbb{E}_i^Q(R_T^2)}{\mathbb{E}_i^Q(R_T)}$ and

If $\frac{M'_T[R_T]}{M_T[R_T]} + \frac{n}{R_T} \geq 0$, then $\mathbb{E}_i^\mathcal{P}(R^n_T) \leq \frac{\mathbb{E}_i^Q(R^n_T) - \mathbb{E}_i^Q(R_T^2)}{\mathbb{E}_i^Q(R_T)}$.

**Proof:** The result follows from Lemma 1 and the steps in Appendix D. □

Consider equation (20) of Result 3 corresponding to $n = 1$:

$$\text{If } \frac{M'_T[R_T]}{M_T[R_T]} + \frac{1}{R_T} \leq 0, \text{ then } \mathbb{E}_i^\mathcal{P}(R_T) \geq \frac{\mathbb{E}_i^Q(R_T)}{\mathbb{E}_i^Q(R_T)}.$$  (22)

This restriction implies a conditional lower bound $\mathbb{E}_i^\mathcal{P}(R_T) \geq \frac{\mathbb{E}_i^Q(R_T) - (\mathbb{E}_i^Q(R_T))^2 + (\mathbb{E}_i^Q(R_T))^2}{\mathbb{E}_i^Q(R_T)}$ (observed at time $t$), and, hence, $\mathbb{E}_i^\mathcal{P}(R_T) - R_{f,t} \geq R^{-1}_{f,t} \text{var}^Q_i(R_T)$, in view of $\mathbb{E}_i^Q(R_T) = R_{f,t}$.

What do we do here that is different from Martin (2017)? Specifically, equation (21) is a new observation and shows that $\mathbb{E}_i^\mathcal{P}(R_T) - R_{f,t} \leq R^{-1}_{f,t} \text{var}^Q_i(R_T)$, so $R^{-1}_{f,t} \text{var}^Q_i(R_T)$ represents an upper bound, when $\frac{M'_T[R_T]}{M_T[R_T]} + \frac{1}{R_T} \geq 0$ for some theoretically and empirically supportable $M_T[R_T]$. Since the sign of $\frac{M'_T[R_T]}{M_T[R_T]} + \frac{1}{R_T}$ could potentially alternate through (calendar) time, our characterizations do not preclude the possibility that $R^{-1}_{f,t} \text{var}^Q_i(R_T)$ represents an upper bound on the expected
excess return at some time $t$, while it could represent a lower bound at some other time $t^*$. Such a possibility is at the crux of our theoretical treatment and empirical approach.

The conditions in Result 3 are sufficient, but not necessary. This is because derivatives are local properties. Result 3 is free of distributional assumptions.

4.2 Empirical evidence on the NCC

The hypothesis of the NCC is that the conditional covariance $\text{cov}^p_t(M_T R_T, R_T) \leq 0$ for all $M_T$. Therefore,

we can reject the hypothesis of the NCC if $\text{cov}^p_t(M_T R_T, R_T) > 0$, for some $M_T[R_T]$. (23)

Denoting the conditional covariance by $\mathbb{E}^p_t(\tilde{c}_T)$, where the demeaned cross-product $\tilde{c}_T$ is given by $\tilde{c}_T \equiv \{M_T[R_T] R_T - \mathbb{E}^p_t(M_T[R_T] R_T)\}\{R_T - \mathbb{E}_t(R_T)\}$, the following two comments are in order:

- First, suppose we wish to assess the hypothesis $H$: $\mathbb{E}^p_t(\tilde{c}_T) > 0$. Having infinitely many, but countable, observations of positive $\tilde{c}_T$ does not violate the possibility that $\mathbb{E}^p_t(\tilde{c}_T) \leq 0$.

- Second, suppose we wish to assess the same hypothesis $H$: $\mathbb{E}^p_t(\tilde{c}_T) > 0$ by utilizing the sufficient condition in Result 3; then it seems that we need to test $H^*: \frac{M'_t[R_T]}{M_T[R_T]} + \frac{1}{R_T} > 0$ almost surely. While straightforward, this condition is not easily testable because, even if we have infinitely many, but countable, observations of positive $\frac{M'_t[R_T]}{M_T[R_T]} + \frac{1}{R_T}$, it does not exclude the possibility that $\frac{M'_t[R_T]}{M_T[R_T]} + \frac{1}{R_T} < 0$ almost surely.

Motivated by the discussions above, the next result is at the center of our empirical exercises.

**Result 4** Let $\mathbb{E}^p(.)$ and $\text{cov}^p(.,.)$ denote the unconditional expectation and unconditional covariance, respectively. The following statement is true:

$$\text{cov}^p(M_T[R_T] R_T, R_T) = \mathbb{E}^p(\text{cov}^p_t(M_T[R_T] R_T, R_T)),$$

(24)

**Proof:** By the law of total covariance formula, $\text{cov}^p(M_T[R_T] R_T, R_T) = \mathbb{E}^p(\text{cov}^p_t(M_T[R_T] R_T, R_T)) + \text{cov}^p(\mathbb{E}^p_t(M_T[R_T] R_T), \mathbb{E}^p_t(R_T))$. Since $\mathbb{E}^p_t(M_T[R_T] R_T) = 1$, the result in equation (24) follows. ■
If the NCC holds almost surely, that is, if, \( \text{cov}_T^P(M_T[R_T]R_T, R_T) \leq 0 \) almost surely, then the unconditional covariance \( \text{cov}^P(M_T[R_T]R_T, R_T) \leq 0 \). For ease of comparability of magnitudes across models of \( M_T[R_T] \), we test the hypothesis that

\[ H_0 : \text{NCC}_T \leq 0, \] where NCC\(_T\) is the unconditional correlation between \( M_T[R_T]R_T \) and \( R_T \). (25)

Specifically, if we reject \( H_0 \), then we reject the NCC, meaning that \( \text{cov}_T^P(M_T[R_T]R_T, R_T) > 0 \) holds with a strictly positive probability.

We next present empirical evidence (using data from options on the market index) from three models. While one could feature more models of \( M_T \), we highlight settings that are theoretically and empirically revealing and amenable to implementation and validation.

**Model A:** The projected SDF depends linearly on the gross return of the market and the gross return of an at-the-money straddle, as follows:

\[
M_T[R_T] = Z_T^\top[R_T] \alpha \quad \text{with} \quad Z_T[R_T] = \begin{pmatrix} R_T \\ R_T^{\text{straddle}} \end{pmatrix} \quad \text{and} \quad \alpha = \left\{ \mathbb{E}^P(Z_T^\top[R_T]Z_T[R_T]) \right\}^{-1} \mathbf{1}, \tag{26}
\]

where \( R_T^{\text{straddle}} \equiv \frac{S_t \max(R_T-1,0)+S_t \max(1-R_T,0)}{\text{call}_{t,T}[S_t]+\text{put}_{t,T}[S_t]} \). We enforce \( \mathbb{E}^P(M_T[R_T]Z_T[R_T]) = 1 \).

**Model B:** The projected SDF depends on the gross return of the market and the gross return of a 2\% out-of-the-money strangle, defined as \( R_T^{\text{strangle}} \equiv \frac{S_t \max(R_T-e^{-0.02},0)+S_t \max(e^{-0.02}-R_T,0)}{\text{call}_{t,T}[S_t e^{-0.02}]+\text{put}_{t,T}[S_t e^{-0.02}]} \), as follows:

\[
M_T[R_T] = \alpha_{\text{market}} R_T + \alpha_{\text{strangle}} R_T^{\text{strangle}}. \tag{27}
\]

Models A and B are distinct since \( R_T^{\text{straddle}} \) and \( R_T^{\text{strangle}} \) are imperfectly correlated.

**Model C:** The projected SDF is exponential in the excess returns of the squared log contract, allowing for asymmetric effect of variance in down and up equity markets:

\[
M_T[R_T] = \exp \left( \eta_{\text{variance}}^+ \mathbb{1}_{\{R_T<1\}} + \eta_{\text{variance}}^- \mathbb{1}_{\{R_T>1\}} \right) (R_T^{\text{variance}} - R_{f,t}) \right\}. \tag{28}
\]
The gross return, $R_T^{\text{variance}}$, is based on the payoff of the following squared log contract:

$$R_T^{\text{variance}} = \frac{\{\log R_T\}^2}{q_t,\{\log R_T\}^2},$$

(29)

where the price of the squared log contract, $q_t,\{\log R_T\}^2 = R_{f,t}^{-1}\mathbb{E}_t^Q(\{\log R_T\}^2)$, is synthesized as

$$q_t,\{\log R_T\}^2 = \int_{K<S_t} \frac{2(1 - \log \frac{K}{S_t})}{K^2} \text{put}_{t,T}[K] dK + \int_{K>S_t} \frac{2(1 - \log \frac{K}{S_t})}{K^2} \text{call}_{t,T}[K] dK.$$

(30)

In our exercises, we use standard procedures to compute the parameters affecting $M_T[R_T]$ and $\text{cov}^F(M_T[R_T] R_T, R_T)$ (see the note to the Tables). Tables 3 and 4 present our findings from implementing Models A, B, and C, respectively. The takeaway is that the correlation between $M_T[R_T]$ and $R_T$; that is, NCC$_T$ is positive. For Models A and B, we additionally verified that $M_T[R_T]$ does not attain negative values (i.e., the minimum $M_T[R_T]$ is positive).

The methodological appeal of Result 4 is that the sign of the expected conditional covariance between $M_T[R_T] R_T$ and $R_T$ can be ascertained by the sign of the unconditional covariance between $M_T[R_T] R_T$ and $R_T$. The conclusion to draw is that the NCC fails to hold even on average.

Elaborating on these findings, we pose $\text{cov}^F(M_T[R_T] R_T, R_T)$ being negative as an explicit hypothesis and consider a bootstrap procedure. We bootstrap (with replacement) the gross returns in $Z_T[R_T]$ and reestimate $\alpha$ in the context, for example, of Models A and B, and Table 3. Then we reconstruct $M_T[R_T] = Z_T^T[R_T] \alpha$ and $R_T$. The 5th and 95th bootstrap values for NCC$_T$ are positive, and we can reject the hypothesis of the NCC.

Our evidence, thus, refutes the notion that the NCC holds point by point and that $R_{f,t}^{-1} \text{var}^Q_t(R_T)$ is a universal lower bound across all plausible $M_T$. In essence, there is evidence, from Tables 3 and 4, that the NCC is not a generic property, and, consequently, $R_{f,t}^{-1} \text{var}^Q_t(R_T)$ may sometimes be an upper bound and not a lower bound.

What is special about featured Models A, B, and C? The distinguishing attribute is the dependence of $M_T[R_T]$ on a specific convex function (i.e., $M_T''[R_T] = \frac{d^2M_T[R_T]}{dR_T^2} > 0$) of $R_T$ that manifests decreasing and increasing regions. For example, $M_T[R_T]$ tends to be high when $R_T^{\text{traddle}}$ or $R_T^{\text{strangle}}$ are high, which, intuitively, reflects sensitivity to market volatility. $M_T[R_T]$ with the said properties
has empirical support,\(^1\) and is consistent with the empirical observation of negative average returns of call options on the market index (e.g., Bakshi, Madan, and Panayotov (2010)). These considered model classes can be differentiated from the ones in Martin (2017) that he employs to convey the empirical relevance of the NCC.

4.3 Additional economic rationale and counterexamples where the NCC fails

In light of equations (20)–(21) evaluated at \( n = 1 \), we consider \( \frac{M_T'[R_T]}{M_T[R_T]} + \frac{1}{R_T} \) and develop example economies in which \( \frac{1}{R_T} \) is sufficiently positive to counteract the possible negative value of \( \frac{M_T'[R_T]}{M_T[R_T]} \).

**Counterexample 1** Suppose

\[
M_T[R_T] = \exp(m_0 - 1 + \Lambda_{\text{straddle}}(R_T^{\text{straddle}} - R_{f,t})), \quad \text{with } \Lambda_{\text{straddle}} > 0. \tag{31}
\]

This projected SDF depends on the excess return of a variable that is sensitive to volatility, has a decreasing region, has an increasing region, and is convex in \( R_T \). Then

\[
\frac{M_T'[R_T]}{M_T[R_T]} + \frac{1}{R_T} = \begin{cases} 
\Lambda_{\text{straddle}} \frac{S_t}{\text{call}_{t,T}[S_t]+\text{put}_{t,T}[S_t]} + \frac{1}{R_T} > 0 & \text{if } R_T > 1, \\
-\Lambda_{\text{straddle}} \frac{S_t}{\text{call}_{t,T}[S_t]+\text{put}_{t,T}[S_t]} + \frac{1}{R_T} & \text{if } R_T < 1.
\end{cases} \tag{32}
\]

Additionally, \( \frac{M_T'[R_T]}{M_T[R_T]} + \frac{1}{R_T} \) can also be determined to be positive in the region \( R_T < 1 \), when \( \Lambda_{\text{straddle}} < \frac{\text{call}_{t,T}[S_t]+\text{put}_{t,T}[S_t]}{S_t} \). ♠

**Counterexample 2** Suppose, for constants \( m_0, \upsilon > 0 \), and \( \delta > 0 \),

\[
M_T[R_T] = \exp \left( m_0 - 1 + \frac{\upsilon}{2} \left( \frac{R_T^2}{q_{t,(R_T^2)}} - R_{f,t} \right) + \delta \left( \frac{R_T}{q_{t,\{R_T\}}} - R_{f,t} \right) \right), \quad \text{for } R_T \in [R, \overline{R}], \tag{33}
\]

where \( R > 0 \) and \( \overline{R} < \infty \).

Here \((\frac{R^2_T}{q_{t,(R^2_T)}} - R_{f,t})\) and \((\frac{\frac{1}{R_T}}{q_{t,(\frac{1}{R_T})}} - R_{f,t})\) are excess returns, where

\[ q_{t,(R^2_T)} = R^{-1}_{f,t} E^Q_t(R^2_T) \]

(respectively, \(q_{t,(\frac{1}{R_T})} = R^{-1}_{f,t} E^Q_t(R^{-1}_T)\)) is the price of the payoff \(R^2_T\) (respectively, \(\frac{1}{R_T}\)) and can be synthesized via a static positioning in options. Then

\[
\frac{M'_T[R_T]}{M_T[R_T]} + \frac{1}{R_T} = \frac{v}{q_{t,(R^2_T)}} R^3_T + R_T - \frac{\delta}{q_{t,(\frac{1}{R_T})}}. \tag{34}
\]

With \(v > 0\), \(vR^3_T + R_T\) is strictly increasing in \(R_T\), which implies that the equation \(vR^3_T + R_T - \frac{\delta}{q_{t,(\frac{1}{R_T})}} = 0\) has a unique real solution given by (see Weisstein (2010, equation (80)))

\[
R^\text{critical}_T = -2\sqrt{\frac{q_{t,(R^2_T)}}{3v}} \sinh \left( \frac{1}{3} \text{arcsinh} \left( -\frac{3\delta}{2v} \sqrt{\frac{3v}{q_{t,(R^2_T)}}} \right) \right). \tag{35}
\]

\(R^\text{critical}_T\) is crucial for determining the sign of \(\frac{M'_T[R_T]}{M_T[R_T]} + \frac{1}{R_T}\) and, thus, of \(\text{cov}_t^P(M_T[R_T],R_T)\).

Suppose \(R^\text{critical}_T < R\). Then, since \(R_T \in [R, \bar{R}]\), we have \(R_T > R^\text{critical}_T\), and the numerator of equation (34) is positive. Therefore, \(\text{cov}_t^P(M_T[R_T],R_T) > 0\) and the NCC is violated. ♣

**Counterexample 3** Suppose \(M_T[R_T]\) is the *weighted* sum of a completely monotone function and an absolutely monotone function (motivated by Bakshi, Madan, and Panayotov (2010)) of the type

\[ M_T[R_T] = w R^{\theta}_T + (1-w) \left( \frac{1}{R_T} \right)^{-\theta} \]

for some constants \(\theta > 1\) and \(0 < w < 1\). \tag{36}

This \(M_T[R_T]\) is convex in \(R_T\), and is negatively (positively) sloped at low (large) \(R_T\), with \(\left( \frac{1}{R_T} \right)^{-\theta}\) reflecting the marginal utility of agents long the *inverse of the market* (i.e., their wealth declines in the region \(R_T > 1\)). We have,

\[
\frac{M'_T[R_T]}{M_T[R_T]} + \frac{1}{R_T} = \frac{\theta}{R_T} \left\{ -w R^{-\theta}_T + (1-w) R^\theta_T \right\} + \frac{1}{R_T} > 0, \quad \text{when} \quad R_T > \left( \frac{w (\theta - 1)}{(1-w)(\theta + 1)} \right)^\frac{1}{2\theta}. \tag{37}
\]

Thus, \(\text{cov}_t^P(M_T[R_T],R_T)\) can be positive, which poses a challenge to the notion of the NCC. ♣

The class of \(M_T\) violating the NCC are theoretically and empirically tenable.
5 Conclusions

What is the compensation that agents require for investing in the equity market? Martin (2017) shows that a lower bound to the expected excess return of the market (and, thus, the minimum compensation) is equal to the discounted risk-neutral variance of the market return. The critical assumption that delivers this lower bound formula is the negative correlation condition (NCC); that is, \( \text{cov}^P_{t}(M_{T} R_{T}, R_{T}) \leq 0 \) for all SDFs \( M_{T} \).

What are the differentiating elements of our paper? Most crucially, we go beyond a lower bound characterization and propose an analytical expression for the conditional expected excess return of the market. Our formula distills the manner in which each risk-neutral return central moment contributes to the expected excess return of the market. Each source of the conditional expected excess return can be tractably extracted from known option prices.

Using data on S&P 500 index options from January 1990 to December 2018 (29 years, 348 option expiration cycles), our empirical exercises emphasize two insights. First, the components related to risk-neutral return variance and risk-neutral return skewness are the essential drivers of the expected excess return of the market. Second, our estimates of the conditional expected excess return materially differ from Martin (2017), and, on average, are twice the size of the lower bound (i.e., the discounted risk-neutral variance).

We take two perspectives to reconcile our findings. First, addressing theoretical distinctions, our formula assigns a weight to each risk-neutral return central moment. Our methodology is new and we do not rely on the assumption that \( \text{cov}^P_{t}(M_{T} R_{T}, R_{T}) \leq 0 \) (i.e., that the NCC holds) to derive our formula. Second, we develop the asset-pricing restrictions of the NCC and provide evidence that the NCC is neither a generic property of the models nor does it necessarily hold in the data. Our theoretical and empirical treatment implies that discounted risk-neutral variance, identified as the lower bound in Martin (2017), could be an upper bound when the NCC fails.

The central problem of determining the expected excess return of the market — as rooted in the tradition of Merton (1980) and Black (1993) — is still hungry for consensus and resolution. Our explicit expression, analytical in quantities inferred from option prices, is a step in that direction.
References


Appendix: Proof of Results

A  Appendix A: Proof of the expected excess return formula (4) in Result 1

For ease of reference, we collect the following notations to keep the steps of our proof self-contained:

\[ r_T \equiv R_T - 1 = \text{net return of the equity market index}; \]

\[ r_{f,t} \equiv R_{f,t} - 1 = \text{net risk-free return}; \]

\[ \Omega \equiv \{ r_T > -1 \} = \text{set of return possibilities}; \]

\[ p[r_T] = \text{density of } r_T \text{ under the real-world probability measure, } P; \]

\[ q[r_T] = \text{density of } r_T \text{ under the risk-neutral probability measure, } Q; \]

\[ \text{mgf}_P^T[\lambda] = \int_{\Omega} e^{\lambda r_T} p[r_T] dr_T = \text{moment-generating function of the real-world distribution}; \]

\[ \text{mgf}_Q^T[\lambda] = \int_{\Omega} e^{\lambda r_T} q[r_T] dr_T = \text{moment-generating function of the risk-neutral distribution}; \]

\[ \text{cmoment}^Q_{n,t}(r_T) = \text{conditional } n\text{-th return central moment under the risk-neutral measure } Q. \]

In light of equation (3), we represent \( M_T[R_T] = M_T[1 + r_T] = N_T[r_T] \), that is,

\[ N_T[r_T] = \exp(m_0 - 1 - \phi(r_T - r_{f,t})) \equiv a_0 e^{-\phi r_T}, \quad \text{where } a_0 \equiv \exp(m_0 - 1 + \phi r_{f,t}). \quad (A1) \]

The constant \( a_0 \) will turn out to be irrelevant in our calculations.

Next, to derive analytical results in the context of a projected \( M_T[R_T] \), or \( N_T[r_T] \), observe from Harrison and Kreps (1979), that one can hypothesize that

\[ \frac{q[r_T]}{p[r_T]} = N_T[r_T], \quad \text{for some positive function}. \quad (A2) \]

We make the normalization such that \( p[r_T] \) integrates to unity, that is,

\[ p[r_T] = \frac{\frac{1}{N_T[r_T]} q[r_T]}{\int_{\Omega} \frac{1}{N_T[r_T]} q[r_T] dr_T}, \quad (A3) \]

which implies that \( \int_{\Omega} p[r_T] dr_T = 1 \).
The $n$-th order raw conditional return moments of the distribution, under $P$ and $Q$, are

$$
\mu_P^n \equiv \int_{\Omega} \{r_T\}^n p(r_T) \, dr_T \quad \text{and} \quad \mu_Q^n \equiv \int_{\Omega} \{r_T\}^n q(r_T) \, dr_T.
$$

(A4)

We denote the moment-generating functions under $P$ and $Q$, as \(\text{mgf}_t^P[\lambda]\) and \(\text{mgf}_t^Q[\lambda]\), respectively. Assume \(\text{mgf}_t^P[\lambda] < \infty\) and \(\text{mgf}_t^Q[\lambda] < \infty\). Then,

$$
\text{mgf}_t^P[\lambda] \equiv \int_{\Omega} e^{\lambda r_T} p(r_T) \, dr_T = 1 + \frac{\lambda}{1!} \mu_P^1 + \frac{\lambda^2}{2!} \mu_P^2 + \frac{\lambda^3}{3!} \mu_P^3 + \frac{\lambda^4}{4!} \mu_P^4 + \ldots, \quad \text{for } \lambda \in \mathbb{R},
$$

(A5)

$$
\text{mgf}_t^Q[\lambda] \equiv \int_{\Omega} e^{\lambda r_T} q(r_T) \, dr_T = 1 + \frac{\lambda}{1!} \mu_Q^1 + \frac{\lambda^2}{2!} \mu_Q^2 + \frac{\lambda^3}{3!} \mu_Q^3 + \frac{\lambda^4}{4!} \mu_Q^4 + \ldots, \quad \text{for } \lambda \in \mathbb{R}.
$$

(A6)

Now consider

$$
\text{mgf}_t^P[\lambda] = \int_{\Omega} e^{\lambda r_T} p(r_T) \, dr_T
$$

(A7)

$$
= \int_{\Omega} e^{\lambda r_T} \frac{1}{N_T[r_T]} q(r_T) \, dr_T \quad \text{(using equation (A3))}
$$

(A8)

$$
= \int_{\Omega} e^{\lambda r_T} e^{\phi r_T} q(r_T) \, dr_T \quad \text{(using equation (A1))}
$$

(A9)

$$
= \frac{\text{mgf}_t^Q[\lambda + \phi]}{\text{mgf}_t^Q[\phi]}.
$$

(A10)

Taking logs on both sides of equation (A10), we arrive at

$$
\log \text{mgf}_t^P[\lambda] = \log \text{mgf}_t^Q[\lambda + \phi] - \log \text{mgf}_t^Q[\phi].
$$

(A11)

Equation (A11) implies that the cumulant-generating functions are related by the following identity:

$$
\widehat{C}_t^P[\lambda] = \widehat{C}_t^Q[\lambda + \phi] - \widehat{C}_t^Q[\phi], \quad \text{where from Kendall and Stuart (1963),}
$$

(A12)

$$
\log \text{mgf}_t^P[\lambda] \equiv \widehat{C}_t^P[\lambda] = \kappa_1^P \frac{\lambda}{1!} + \kappa_2^P \frac{\lambda^2}{2!} + \kappa_3^P \frac{\lambda^3}{3!} + \kappa_4^P \frac{\lambda^4}{4!} + \ldots = \sum_{n=1}^{\infty} \kappa_n^P \frac{\lambda^n}{n!}
$$

(A13)

$$
\log \text{mgf}_t^Q[\lambda] \equiv \widehat{C}_t^Q[\lambda] = \kappa_1^Q \frac{\lambda}{1!} + \kappa_2^Q \frac{\lambda^2}{2!} + \kappa_3^Q \frac{\lambda^3}{3!} + \kappa_4^Q \frac{\lambda^4}{4!} + \ldots = \sum_{n=1}^{\infty} \kappa_n^Q \frac{\lambda^n}{n!}.
$$

(A14)
Following Kendall and Stuart (1963, page 73, eq. (3.43)), \( \kappa_n^\mathbb{P} \) are cumulants under \( \mathbb{P} \), defined in relation to the raw moments, as

\[
\kappa_1^\mathbb{P} \equiv \mu_1^\mathbb{P} = \mathbb{E}_t^\mathbb{P}(r_T),
\]

(A15)

\[
\kappa_2^\mathbb{P} \equiv \mu_2^\mathbb{P} - (\mu_1^\mathbb{P})^2,
\]

(A16)

\[
\kappa_3^\mathbb{P} \equiv \mathbb{E}_t^\mathbb{P}(\{r_T - \mu_1^\mathbb{P}\}^3),
\]

(A17)

\[
\kappa_4^\mathbb{P} \equiv \mathbb{E}_t^\mathbb{P}(\{r_T - \mu_1^\mathbb{P}\}^4) - 3(\kappa_3^\mathbb{P})^2,
\]

(A18)

\[
\kappa_5^\mathbb{P} \equiv \mathbb{E}_t^\mathbb{P}(\{r_T - \mu_1^\mathbb{P}\}^5) - 10\kappa_3^\mathbb{P}\kappa_2^\mathbb{P}.
\]

(A19)

Under the risk-neutral probability measure \( \mathbb{Q} \), the corresponding cumulants are

\[
\kappa_1^\mathbb{Q} \equiv \mu_1^\mathbb{Q} = \mathbb{E}_t^\mathbb{Q}(r_T) = r_{f,t},
\]

(A20)

\[
\kappa_2^\mathbb{Q} \equiv \mu_2^\mathbb{Q} - (\mu_1^\mathbb{Q})^2 = \mathbb{E}_t^\mathbb{Q}(\{r_T - \mu_1^\mathbb{Q}\}^2) = \text{var}_t^\mathbb{Q}(r_T),
\]

(A21)

\[
\kappa_3^\mathbb{Q} \equiv \mathbb{E}_t^\mathbb{Q}(\{r_T - \mu_1^\mathbb{Q}\}^3) = (\text{var}_t^\mathbb{Q}(r_T))^{3/2}\text{Skewness}_t^\mathbb{Q}(r_T),
\]

(A22)

\[
\kappa_4^\mathbb{Q} \equiv \mathbb{E}_t^\mathbb{Q}(\{r_T - \mu_1^\mathbb{Q}\}^4) - 3(\kappa_3^\mathbb{Q})^2 = (\text{var}_t^\mathbb{Q}(r_T))^2(\text{Kurtosis}_t^\mathbb{Q}(r_T) - 3), \quad \text{and}
\]

(A23)

\[
\kappa_5^\mathbb{Q} \equiv \mathbb{E}_t^\mathbb{Q}(\{r_T - \mu_1^\mathbb{Q}\}^5) - 10\kappa_3^\mathbb{Q}\kappa_2^\mathbb{Q} = (\text{var}_t^\mathbb{Q}(r_T))^{5/2}(\text{Hskewness}_t^\mathbb{Q}(r_T) - 10\text{Skewness}_t^\mathbb{Q}(r_T)).
\]

(A24)

Hskewness\(_t^\mathbb{Q}(r_T)\) is the risk-neutral hyperskewness, defined in equation (A39). Our analysis does not require a parametric assumption about the risk-neutral distribution.

We are ready to verify Result 1. The conditional expected return under the \( \mathbb{P} \) measure is

\[
\mathbb{E}_t^\mathbb{P}(r_T) = \left. \frac{d\mathbb{C}_t^\mathbb{P}[\lambda]}{d\lambda} \right|_{\lambda=0} \quad \text{(now use equation (A12))}
\]

(A25)

\[
= \left. \frac{d\mathbb{C}_t^\mathbb{Q}[\lambda + \phi]}{d\lambda} \right|_{\lambda=0} - \left. \frac{d\mathbb{C}_t^\mathbb{Q}[\phi]}{d\lambda} \right|_{\lambda=0}
\]

(A26)

\[
= \frac{1}{t!}\kappa_1^\mathbb{Q} + 2\frac{\phi}{2!}\kappa_2^\mathbb{Q} + 3\frac{\phi^2}{3!}\kappa_3^\mathbb{Q} + 4\frac{\phi^3}{4!}\kappa_4^\mathbb{Q} + 5\frac{\phi^4}{5!}\kappa_5^\mathbb{Q} + \sum_{n=6}^{\infty} \frac{\phi^{n-1}}{(n-1)!} \kappa_n^\mathbb{Q},
\]

(A27)

where we have exploited the derivative \( \frac{d\mathbb{C}_t^\mathbb{Q}[\lambda + \phi]}{d\lambda} = \kappa_1^\mathbb{Q}\frac{1}{t!} + 2\kappa_2^\mathbb{Q}\frac{(\lambda + \phi)^2}{2!} + 3\kappa_3^\mathbb{Q}\frac{(\lambda + \phi)^3}{3!} + 4\kappa_4^\mathbb{Q}\frac{(\lambda + \phi)^4}{4!} + \ldots \).
Noting that $\kappa_1^Q = \mathbb{E}_t^Q(r_T) = \mathbb{E}_t^Q(R_T - 1) = R_{f,t} - 1 = r_{f,t}$, the net risk-free return, it follows from equation (A27) that

$$E_t^P(R_T) - R_{f,t} = \phi \kappa_2^Q + \frac{\phi^2}{2} \kappa_3^Q + \frac{\phi^3}{6} \kappa_4^Q + \frac{\phi^4}{24} \kappa_5^Q + \sum_{n=6}^{\infty} \frac{\phi^{n-1}}{(n-1)!} \kappa_n^Q. \quad (A28)$$

The conditional expected excess return in equation (A28) can be equivalently written as

$$E_t^P(R_T) - R_{f,t} = \frac{1}{\phi} (\{\phi SD_t^Q(r_T)\}^2 + \frac{1}{2} \{\phi SD_t^Q(r_T)\}^3 \text{Skewness}_t^Q(r_T)$$

$$+ \frac{1}{6} \{\phi SD_t^Q(r_T)\}^4 (\text{Kurtosis}_t^Q(r_T) - 3)$$

$$+ \frac{1}{24} \{\phi SD_t^Q(r_T)\}^5 (\text{Hskewness}_t^Q(r_T) - 10 \text{Skewness}_t^Q(r_T)) + ...) \quad (A29),$$

where $SD_t^Q(r_T) = \sqrt{\text{var}_t^Q(r_T)}$, Skewness$_t^Q(r_T)$, Kurtosis$_t^Q(r_T)$, and Hskewness$_t^Q(r_T)$ are the conditional risk-neutral volatility, skewness, kurtosis, and hyperskewness, respectively.

The final step is to infer the risk-neutral return central moments from option prices, known at time $t$. Specifically, let

$$\text{cmoment}_{n,t}^Q \equiv \mathbb{E}_t^Q((r_T - r_{f,t})^n) = \mathbb{E}_t^Q((R_T - (R_{f,t} - 1))^n) \quad (A30)$$

$$= \mathbb{E}_t^Q((\frac{S_{t+T}}{S_t} - R_{f,t})^n) \quad (A31)$$

$$= \frac{n(n-1)R_{f,t}}{S_t^2} \int_{K<R_{f,t}S_t} (\frac{K}{S_t} - R_{f,t})^{n-2} \text{put}_{t,T}[K] dK$$

$$+ \frac{n(n-1)R_{f,t}}{S_t^2} \int_{K>R_{f,t}S_t} (\frac{K}{S_t} - R_{f,t})^{n-2} \text{call}_{t,T}[K] dK. \quad (A32)$$

We can move from equation (A31) to equation (A32) since, from Bakshi and Madan (2000, Appendix A.3) and Carr and Madan (2001, equation (2)), we have, for $n \geq 2$,

$$A[S_{t+T}] \equiv (\frac{S_{t+T}}{S_t} - R_{f,t})^n \quad (A33)$$

$$= A[S_{t+T}]_{S_{t+T}=R_{f,t}S_t} + \frac{A'[S_{t+T}]_{S_{t+T}=R_{f,t}S_t}}{0} (S_{t+T} - S_t)$$

$$+ \int_{K<R_{f,t}S_t} A''[K](K - S_{t+T})^+ dK + \int_{K>R_{f,t}S_t} A''[K](S_{t+T} - K)^+ dK, \quad (A34)$$
where

\[
A''[K] = \frac{d^2 A[S_{t+T}]}{dS_{t+T}^2} \bigg|_{S_{t+T}=K} = \frac{n(n-1)}{S_t^2} \left( \frac{S_{t+T}}{S_t} - R_{f,t} \right)^{n-2} \bigg|_{S_{t+T}=K} = \frac{n(n-1)}{S_t^2} \left( \frac{K}{S_t} - R_{f,t} \right)^{n-2}.
\]  

(A35)

We obtain

\[
SD_t^Q(r_T) = \sqrt{\text{cmoment}_{n,t}^Q|_{n=2}},
\]

(A36)

\[
\text{Skewness}_t^Q(r_T) = \frac{\text{cmoment}_{n,t}^Q|_{n=3}}{\{SD_t^Q(r_T)\}^3},
\]

(A37)

\[
\text{Kurtosis}_t^Q(r_T) = \frac{\text{cmoment}_{n,t}^Q|_{n=4}}{\{SD_t^Q(r_T)\}^4}, \quad \text{and}
\]

(A38)

\[
\text{Hskewness}_t^Q(r_T) = \frac{\text{cmoment}_{n,t}^Q|_{n=5}}{\{SD_t^Q(r_T)\}^5}.
\]

(A39)

The right-hand side of equation (A29) involves quantities inferrable from option prices. ■

B  Appendix B: Proof of the expected excess return formula (9) in Result 2

In analogy to equations (A7)–(A10) and with \( H[r_T] = \frac{1}{M_T[R_T]} = \frac{1}{M_T[1+r_T]} \in C^\infty \), we consider

\[
\text{mgf}_t^Q[^\lambda] = \int_\Omega e^{\lambda r_T} p[r_T] dr_T = \int_\Omega e^{\lambda r_T} \frac{H[r_T]}{\int_\Omega H[r_T] q[r_T] dr_T} q[r_T] dr_T \quad \text{(using equation (A3))}
\]

(B1)

\[
= \int_\Omega e^{\lambda r_T} \frac{H[r_T]}{\int_\Omega H[r_T] q[r_T] dr_T} q[r_T] dr_T = \frac{\text{E}_t^Q(\exp^{\lambda r_T} H[r_T])}{\text{E}_t^Q(H[r_T])}.
\]

(B2)

To express \( \text{E}_t^P(R_T - R_{f,t}) \) in terms of risk-neutral cumulants, we write equation (B3) as

\[
\text{mgf}_t^F[^\lambda] = \frac{\text{E}_t^Q(\exp^{\lambda (r_T-R_{f,t})} H[r_T])}{\text{E}_t^Q(\exp^{-\lambda r_{f,t}} H[r_T])}.
\]

(B3)

Hence, we obtain

\[
\log \text{mgf}_t^F[^\lambda] = \log \frac{\text{E}_t^Q(\exp^{\lambda (r_T-R_{f,t})} H[r_T])}{\text{E}_t^Q(\exp^{-\lambda r_{f,t}} H[r_T])} = \log \text{E}_t^Q(H[r_T]) + \lambda r_{f,t}.
\]

(B4)

\[
\log \text{mgf}_t^F[^\lambda] = \log \text{E}_t^Q(\exp^{\lambda (r_T-R_{f,t})} H[r_T]) - \log \text{E}_t^Q(H[r_T]) + \lambda r_{f,t}.
\]
It follows that

\[
\mathbb{E}_t^Q (r_T) = \frac{d \log \operatorname{mgf}_t^Q [\lambda]}{d \lambda} \bigg|_{\lambda=0} + r_{f,t}. 
\]  

(B6)

Next, we employ the fact that \( e^{\lambda (r_T - r_{f,t})} = 1 + \lambda (r_T - r_{f,t}) + \frac{\lambda^2}{2} (r_T - r_{f,t})^2 + \frac{\lambda^3}{3!} (r_T - r_{f,t})^3 + \frac{\lambda^4}{4!} (r_T - r_{f,t})^4 + \cdots \), and \( H[r_T] = H[r_{f,t}] + H'[r_{f,t}](r_T - r_{f,t}) + \frac{H''[r_{f,t}]}{2} (r_T - r_{f,t})^2 + \frac{H'''[r_{f,t}]}{3!} (r_T - r_{f,t})^3 + \frac{H''''[r_{f,t}]}{4!} (r_T - r_{f,t})^4 + \cdots \). Furthermore, assuming that one can switch the order of taking expectations and the infinite summations of the terms in the Taylor series expansion, we note that

\[
\mathbb{E}_t^Q (e^{\lambda (r_T - r_{f,t})} H[r_T]) = \mathbb{E}_t^Q (\{1 + \lambda (r_T - r_{f,t}) + \frac{\lambda^2}{2} (r_T - r_{f,t})^2 + \frac{\lambda^3}{3!} (r_T - r_{f,t})^3 + \frac{\lambda^4}{4!} (r_T - r_{f,t})^4 + \cdots \}\{H[r_{f,t}] + H'[r_{f,t}](r_T - r_{f,t}) + \frac{H''[r_{f,t}]}{2} (r_T - r_{f,t})^2 + \frac{H'''[r_{f,t}]}{3!} (r_T - r_{f,t})^3 + \frac{H''''[r_{f,t}]}{4!} (r_T - r_{f,t})^4 + \cdots \}),
\]  

(B8)

\[
= c_0 + c_1 [\lambda] (\kappa_1^Q - \kappa_1) + c_2 [\lambda] \kappa_2^Q + c_3 [\lambda] \kappa_3^Q + c_4 [\lambda] \{\kappa_4^Q + 3(\kappa_2^Q)^2\} + \cdots
\]  

(B9)

\[
= c_0 (1 + \frac{1}{c_0} \{c_2 [\lambda] \kappa_2^Q + c_3 [\lambda] \kappa_3^Q + c_4 [\lambda] \{\kappa_4^Q + 3(\kappa_2^Q)^2\} + \cdots \}) = x[\lambda]
\]  

(B10)

In deriving equation (B9), the cumulants under \( Q \) are defined as \( \kappa_1^Q = \mathbb{E}_t^Q (r_T) = r_{f,t} \), \( \kappa_2^Q = \mathbb{E}_t^Q (\{r_T - \mu_1^Q\}^2) \), \( \kappa_3^Q = \mathbb{E}_t^Q (\{r_T - \mu_1^Q\}^3) \), and \( \kappa_4^Q = \mathbb{E}_t^Q (\{r_T - \mu_1^Q\}^4) - 3(\kappa_2^Q)^2 \).

Each \( c_j [\lambda] \) (for \( j = 1, 2, \ldots \)) in equation (B9) depends on \( \lambda \), where for example,

\[
c_0 = H[r_{f,t}],
\]  

(B11)

\[
c_1 [\lambda] = \lambda H[r_{f,t}] + H'[r_{f,t}],
\]  

(B12)

\[
c_2 [\lambda] = \frac{\lambda^2 H[r_{f,t}]}{2} + \frac{\lambda H''[r_{f,t}]}{2} + \frac{H'''[r_{f,t}]}{6},
\]  

(B13)

\[
c_3 [\lambda] = \frac{\lambda^3 H[r_{f,t}]}{6} + \frac{\lambda H''[r_{f,t}]}{2} + \frac{\lambda H'''[r_{f,t}]}{6} + \frac{H''''[r_{f,t}]}{24},
\]  

(B14)

\[
c_4 [\lambda] = \frac{\lambda^4 H[r_{f,t}]}{24} + \frac{\lambda H''[r_{f,t}]}{6} + \frac{\lambda H'''[r_{f,t}]}{6} + \frac{H''''[r_{f,t}]}{24},
\]  

(B15)
Substituting the formula \( \log(1 + x) = x - \frac{x^2}{2} + \frac{x^3}{3} - \frac{x^4}{4} + \ldots \) into equation (B10), we have

\[
\log E_t^Q(e^{\lambda(T-r_{f,t})}) = \log c_0 + \log(1 + x[\lambda]) = \log c_0 + x[\lambda] - \frac{x^2[\lambda]}{2} + \frac{x^3[\lambda]}{3} - \frac{x^4[\lambda]}{4} + \ldots. \tag{B17}
\]

Then, using equation (B7), and rearranging, we have

\[
E_t^p(r_T) - r_{f,t} = \frac{dx[\lambda]}{d\lambda} \bigg|_{\lambda=0} - \frac{1}{2} \frac{dx^2[\lambda]}{d\lambda} \bigg|_{\lambda=0} + \frac{1}{3} \frac{dx^3[\lambda]}{d\lambda} \bigg|_{\lambda=0} - \frac{1}{4} \frac{dx^4[\lambda]}{d\lambda} \bigg|_{\lambda=0} + \cdots \tag{B18}
\]

\[
= H'[\lambda^2]_2^Q + \frac{H''[\lambda^4]}{2} H[\lambda^2] + \frac{H'''[\lambda^6]}{6} H[\lambda^2] \{ \kappa_4^Q + 3(\kappa_2^Q)^2 \} - \left( H'[\lambda^3]_3^Q + \frac{H''[\lambda^5]}{2} H[\lambda^3] \{ \kappa_4^Q + 3(\kappa_2^Q)^2 \} \right) \left( H'[\lambda^2]_2^Q + \frac{H''[\lambda^4]}{6} H[\lambda^2] + \frac{H'''[\lambda^6]}{24} H[\lambda^2] \{ \kappa_4^Q + 3(\kappa_2^Q)^2 \} \right) \]

\[
\cdots.
\]

Assuming \((\kappa_2^Q)^2 \approx 0\) (i.e., ignoring the effect of square of the risk-neutral variance of market return) and some cross-product risk-neutral return moments (i.e., \(\kappa_2^Q \kappa_3^Q \approx 0\), and so on), we see that

\[
E_t^p(R_T - R_{f,t}) = \frac{H'[\lambda^2]_2^Q}{H[\lambda^2]} \kappa_2^Q + \frac{H''[\lambda^4]}{2} \frac{H[\lambda^2]}{H[\lambda^2]} \kappa_3^Q + \frac{H'''[\lambda^6]}{6} \frac{H[\lambda^2]}{H[\lambda^2]} \kappa_4^Q + \cdots. \tag{B19}
\]

Equation (B19) is in agreement with equation (A28), when \(H[\lambda^2] = \frac{1}{M_r[1+r_T]} = \exp(-m_0 + 1 + \phi(r_T - r_{f,t}))\). ■

### C Appendix C: Proof of Lemma 1

In what follows, we suppress the subscript \( T \) on the random variable \( X_T \).

Since \(E_t^p(X)\) is in the domain of \( g \), we have

\[
\text{cov}_t^p(g[X],X) = E_t^p(\{X - E_t^p(X)\}\{g[X] - E_t^p(g[X])\}) \tag{C1}
\]

\[
= E_t^p(\{X - E_t^p(X)\}\{g[X] - g[E_t^p(X)]\}) + E_t^p(\{X - E_t^p(X)\}\{g[E_t^p(X)] - E_t^p(g[X])\})
\]

\[
= E_t^p(\{X - E_t^p(X)\}\{g[X] - g[E_t^p(X)]\}) + \{g[E_t^p(X)] - E_t^p(g[X])\} E_t^p(X - E_t^p(X)) = 0
\]

\[
= E_t^p(\{X - E_t^p(X)\}\{g[X] - g[E_t^p(X)]\}). \tag{C2}
\]
The lemma follows by noticing that if \( g[X] \) is decreasing on \( D \), when \( X \leq (\geq) \mathbb{E}_t^P(X) \), we have \( g[X] \geq (\leq) g[\mathbb{E}_t^P(X)] \), which implies that \((X - \mathbb{E}_t^P(X))(g[X] - g[\mathbb{E}_t^P(X)]) \leq 0 \) everywhere.

Furthermore, if \( g[X] \) is increasing on \( D \), when \( X \leq (\geq) \mathbb{E}_t^P(X) \), we have \( g[X] \leq (\geq) g[\mathbb{E}_t^P(X)] \), which implies that \((X - \mathbb{E}_t^P(X))(g[X] - g[\mathbb{E}_t^P(X)]) \geq 0 \) everywhere. ■

### Appendix D: Proof of Result 3

For brevity, we again suppress the subscript \( T \) on the random variable \( X_T \).

It suffices to notice that if \( g'[X] \leq (\geq) 0 \), then \( g[X] \) is decreasing (increasing).

Apply Lemma 1 by setting, for any positive integer \( n \),

\[
X = R^n_T \quad \text{and} \quad g[X] = M_T[X^{\frac{1}{n}}] X. \tag{D1}
\]

Then

\[
g'[X] = M'_T[X^{\frac{1}{n}}] \frac{1}{n} X^{\frac{1}{n}-1} X + M_T[X^{\frac{1}{n}}] \tag{D2}
\]

\[
= \frac{M'_T[R_T] R_T}{n} + M_T[R_T] \tag{D3}
\]

\[
= \frac{M_T[R_T] R_T}{n} \left( \frac{M'_T[R_T]}{M_T[R_T]} + \frac{n}{R_T} \right). \tag{D4}
\]

Next, to obtain \( \mathbb{E}_t^P(R^n_T) \), notice that

\[
\text{cov}_t^P(M_T[R_T]R^n_T, R^n_T) = \mathbb{E}_t^P(M_T[R_T] R^{2n}_T) - \mathbb{E}_t^P(M_T[R_T] R^n_T) \mathbb{E}_t^P(R^n_T) \tag{D5}
\]

\[
= \mathbb{E}_t^P(M_T[R_T]) \mathbb{E}_t^Q(R^{2n}_T) - \mathbb{E}_t^P(M_T[R_T]) \mathbb{E}_t^Q(R^n_T) \mathbb{E}_t^P(R^n_T) \tag{D6}
\]

\[
= \frac{\mathbb{E}_t^Q(R^{2n}_T)}{R_{f,t}} - \frac{\mathbb{E}_t^Q(R^n_T)}{R_{f,t}} \mathbb{E}_t^P(R^n_T). \tag{D7}
\]

Rearranging,

\[
\mathbb{E}_t^P(R^n_T) = \frac{\mathbb{E}_t^Q(R^{2n}_T) - R_{f,t} \text{cov}_t^P(M_T[R_T] R^n_T, R^n_T)}{\mathbb{E}_t^Q(R^n_T)}. \tag{D8}
\]
In particular, for $n = 1$,

$$
\mathbb{E}_t^P(R_T) = \frac{\mathbb{E}_t^Q(R_T^2) - R_{f,t} \text{cov}_t^P(M_T[R_T] R_T, R_T)}{\mathbb{E}_t^Q(R_T)} \tag{D9}
$$

$$
= R_{f,t} + \frac{\text{var}_t^Q(R_T)}{R_{f,t}} - \text{cov}_t^P(M_T[R_T] R_T, R_T). \tag{D10}
$$

Furthermore, for $n = 2$,

$$
\mathbb{E}_t^P(R_T^2) = \frac{\mathbb{E}_t^Q(R_T^4) - R_{f,t} \text{cov}_t^P(M_T[R_T] R_T^2, R_T^2)}{\mathbb{E}_t^Q(R_T^2)} \tag{D11}
$$

$$
= \frac{\mathbb{E}_t^Q(R_T^4)}{\mathbb{E}_t^Q(R_T^2)} - \frac{R_{f,t}}{\mathbb{E}_t^Q(R_T^2)} \text{cov}_t^P(M_T[R_T] R_T^2, R_T^2). \tag{D12}
$$

We have provided the intermediate steps of the proof. ■
Table 1: Conditional expected excess return of the market

Reported are (i) estimates of \((\phi, m_0)\) of the specification of \(M_T\) in equation (3) and (ii) features of the conditional expected excess return of the market (based on equation (4) of Result 1). We obtain the following estimates of \(\phi\) and \(m_0\) by solving a minimum discrepancy problem:

<table>
<thead>
<tr>
<th></th>
<th>(\phi)</th>
<th>(m_0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>2.274</td>
<td>1.007</td>
</tr>
<tr>
<td>Bootstrap 5th percentile value</td>
<td>1.30</td>
<td>1.002</td>
</tr>
<tr>
<td>Bootstrap 95th percentile value</td>
<td>3.29</td>
<td>1.015</td>
</tr>
</tbody>
</table>

Specifically, one solves \(\inf_{M:\mathcal{M}} \mathbb{E}^p(M \log M)\) with \(\mathcal{M} \equiv \{M > 0 \text{ such that } \mathbb{E}^p(M(R - R_f)) = 0, \mathbb{E}^p(M) = \mathbb{E}^p(R_{f,t}^{-1}) = \mu_M, \text{ and } \mathbb{E}^p(M \log M) < \infty\}\), where \(\mathbb{E}^p(.)\) is unconditional expectation. The solution is \(M^* = \exp(m_0^* - \phi^*(R - R_f))\), where \((\phi^*, m_0^*)\) solve \(\inf_{M:} \{ -m_0 \mu_M + \mathbb{E}^p(\exp(m_0 - 1 - \phi(R - R_f))) \}\) (e.g., Borovička, Hansen, and Scheinkman (2016, Section VIII.B)). The sample period for estimating \(\phi\) is 1926:07 to 2018:12 (1,110 monthly observations). We adopt a bootstrap procedure and draw \((R_{f,t}, R_T)\) with replacement. Then, we reestimate \((\phi, m_0)\). The reported confidence intervals are based on 10,000 bootstrap samples.

For each date \(t\), we compute the conditional expected excess return of the market as

\[
\mathbb{E}^p_t(R_T) - R_{f,t} = \frac{1}{\phi}\left(\{\phi \text{ SD}_t^Q(R_T)\}^2 + \frac{1}{2}\{\phi \text{ SD}_t^Q(R_T)\}^3 \times \text{Skewness}_t^Q(R_T) \right.
\]

\[
+ \frac{1}{6}\{\phi \text{ SD}_t^Q(R_T)\}^4 \times \{\text{Kurtosis}_t^Q(R_T) - 3\} 
\]

\[
+ \frac{1}{24}\{\phi \text{ SD}_t^Q(R_T)\}^5 \{\text{Hskewness}_t^Q(R_T) - 10 \text{ Skewness}_t^Q(R_T)\} + \ldots \right),
\]

where \(\text{SD}_t^Q(R_T) \equiv \sqrt{\text{var}_t^Q(R_T)}\), \(\text{Skewness}_t^Q(R_T)\), \(\text{Kurtosis}_t^Q(R_T)\), and \(\text{Hskewness}_t^Q(R_T)\) are, respectively, the conditional risk-neutral return volatility, skewness, kurtosis, and hyperskewness. The reported features of \(\mathbb{E}^p_t(R_T) - R_{f,t}\) rely on data from the S&P 500 index options market from January 1990 to December 2018 (29 years, 348 option expiration cycles). All reported numbers are in annualized percentage units.

<table>
<thead>
<tr>
<th></th>
<th>Average</th>
<th>SD</th>
<th>5th</th>
<th>50th</th>
<th>95th</th>
</tr>
</thead>
<tbody>
<tr>
<td>(i) Expected excess return of the market (annualized, %)</td>
<td>8.97</td>
<td>9.99</td>
<td>1.8</td>
<td>5.8</td>
<td>26.2</td>
</tr>
<tr>
<td>(ii) $\frac{1}{\phi}{\phi \text{ SD}_t^Q(R_T)}^2 + \frac{1}{2}{\phi \text{ SD}_t^Q(R_T)}^3 \times \text{Skewness}_t^Q(R_T)$</td>
<td>8.91</td>
<td>9.92</td>
<td>1.8</td>
<td>5.8</td>
<td>25.8</td>
</tr>
<tr>
<td>(iii) $\frac{1}{2}{\phi \text{ SD}_t^Q(R_T)}^2$</td>
<td>9.84</td>
<td>11.3</td>
<td>1.9</td>
<td>6.4</td>
<td>30.6</td>
</tr>
<tr>
<td>(iv) $\frac{1}{6}{\phi \text{ SD}_t^Q(R_T)}^4 \times {\text{Kurtosis}_t^Q(R_T) - 3}$</td>
<td>0.497</td>
<td>0.16</td>
<td>-0.1</td>
<td>0.00</td>
<td>0.20</td>
</tr>
<tr>
<td>(v) $\frac{1}{24}{\phi \text{ SD}_t^Q(R_T)}^5 {\text{Hskewness}_t^Q(R_T) - 10 \text{ Skewness}_t^Q(R_T)}$</td>
<td>0.006</td>
<td>0.07</td>
<td>-0.02</td>
<td>-0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>(vi) Martin (2017) lower bound, $R_{f,t}^{-1}\text{var}_t^Q(R_T)$</td>
<td>4.32</td>
<td>4.96</td>
<td>0.8</td>
<td>2.8</td>
<td>13.4</td>
</tr>
<tr>
<td>(vii) ${\mathbb{E}<em>t^p(R_T) - R</em>{f,t}} - {R_{f,t}^{-1}\text{var}_t^Q(R_T)}$</td>
<td>4.64</td>
<td>4.96</td>
<td>1.0</td>
<td>3.0</td>
<td>13.6</td>
</tr>
</tbody>
</table>
Table 2: Estimates of conditional expected excess return of the market from alternative models of $M_T$

Reported are estimates of $(m_0, \phi, \phi_z)$ of the specification of $M_T$ in equation (10); that is, $M_T[R_T] = \exp (m_0 - 1 - \{\phi + \phi_z z_t\}(R_T - R_{f,t}))$. We consider $z_t$ to be either the prior month change in realized market variance or the prior one month return on the HML factor. The market variance is constructed as the sum of daily squared log returns. To estimate $(m_0, \phi, \phi_z)$, one solves $\text{arg inf}_{(m_0, \phi, \phi_z)} \{ -m_0 \mu_M + \mathbb{E}^p(\exp(m_0 - 1 - (\phi + \phi_z z_t)(R - R_{f,t})) \}$, where $\mathbb{E}^p(.)$ is unconditional expectation. The sample period for estimation is 1926:07 to 2018:12 (1,110 monthly observations). We adopt a bootstrap procedure and draw $(R_{f,t}, R_T, z_t)$ with replacement. Then, we reestimate $(m_0, \phi, \phi_z)$. The reported confidence intervals are based on 10,000 bootstrap samples.

<table>
<thead>
<tr>
<th></th>
<th>$z_t$ is change in market variance</th>
<th></th>
<th>$z_t$ is HML</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\phi$</td>
<td>$m_0$</td>
<td>$\phi_z$</td>
</tr>
<tr>
<td>Estimate</td>
<td>2.277</td>
<td>1.005</td>
<td>-50.29</td>
</tr>
<tr>
<td>Bootstrap 5th percentile value</td>
<td>1.372</td>
<td>1.000</td>
<td>-175.38</td>
</tr>
<tr>
<td>Bootstrap 95th percentile value</td>
<td>3.339</td>
<td>1.013</td>
<td>82.20</td>
</tr>
</tbody>
</table>

For each date $t$, we compute the conditional expected excess return of the market using the formula in equation (9) of Result 2. The reported features of $\mathbb{E}^p_t(R_T - R_{f,t})$ rely on data from the S&P 500 index options market from January 1990 to December 2018 (29 years, 348 option expiration cycles). All reported numbers are in annualized percentage units.

<table>
<thead>
<tr>
<th>$\mathbb{E}^p_t(R_T - R_{f,t})$ (annualized, %)</th>
<th>5th</th>
<th>50th</th>
<th>95th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>8.84</td>
<td>9.96</td>
<td></td>
</tr>
<tr>
<td>SD</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentiles</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(i) $z_t$ is change in market variance</td>
<td>1.81</td>
<td>5.7</td>
<td>24.8</td>
</tr>
<tr>
<td>(ii) $z_t$ is HML factor</td>
<td>1.8</td>
<td>5.6</td>
<td>25.9</td>
</tr>
</tbody>
</table>
Table 3: Testing the NCC when $Z_T[R_T]$ contains (i) the gross return of the market and (ii) the gross return of an at-the-money straddle, or a 2% out-of-the-money strangle.

In Model A, the gross returns in $Z_T[R_T]$ are

$$Z_T[R_T] = \begin{pmatrix} R_T \\ R_{straddle}^T \end{pmatrix}, \quad \text{where} \quad R_{straddle}^T = \frac{S_t \max(R_T - 1, 0) + S_t \max(1 - R_T, 0)}{\text{call}_{t,T}[S_t] + \text{put}_{t,T}[S_t]}.$$

In Model B, the gross returns in $Z_T[R_T]$ are

$$Z_T[R_T] = \begin{pmatrix} R_T \\ R_{strangle}^T \end{pmatrix}, \quad \text{where} \quad R_{strangle}^T = \frac{S_t \max(R_T - e^{0.02}, 0) + S_t \max(e^{-0.02} - R_T, 0)}{\text{call}_{t,T}[S_t e^{0.02}] + \text{put}_{t,T}[S_t e^{-0.02}]}.$$

The form of the projected SDF, $M_T[R_T]$, is

$$M_T[R_T] = Z_T^T[R_T] \alpha, \quad \text{and we infer} \quad \alpha = \left\{ \mathbb{E}(Z_T^T[R_T] Z_T[R_T]) \right\}^{-1} 1.$$

Thus, we compute $\alpha$ following Cochrane (2005, pages 65–66). Reported is the unconditional correlation between $M_T[R_T]$ and $R_T$, denoted as NCC$_T$. SD is standard deviation of $M_T[R_T] = Z_T^T[R_T] \alpha$. We adopt a bootstrap procedure and draw $Z_T[R_T]$ with replacement. Then, we reestimate $\alpha$. The reported confidence intervals are based on 10,000 bootstrap samples. All reported results rely on data from the S&P 500 index options market from January 1990 to December 2018 (29 years, 348 option expiration cycles).

### Panel A: $M_T[R_T]$ depends linearly on $R_T$ and $R_{straddle}^T$ (Model A)

<table>
<thead>
<tr>
<th>$\alpha_{\text{market}}$</th>
<th>$\alpha_{\text{straddle}}$</th>
<th>NCC$_T$</th>
<th>Properties of $M_T[R_T] = Z_T^T[R_T] \alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimates</td>
<td>0.73</td>
<td>0.30</td>
<td>0.26 78 0.992 72</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Bootstrap</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>5th</td>
<td>0.61</td>
<td>0.17</td>
<td>0.13 45 0.987 61</td>
</tr>
<tr>
<td>95th</td>
<td>0.83</td>
<td>0.48</td>
<td>0.49 114 0.997 82</td>
</tr>
</tbody>
</table>

### Panel B: $M_T[R_T]$ depends linearly on $R_T$ and $R_{strangle}^T$ (Model B)

<table>
<thead>
<tr>
<th>$\alpha_{\text{market}}$</th>
<th>$\alpha_{\text{strangle}}$</th>
<th>NCC$_T$</th>
<th>Properties of $M_T[R_T] = Z_T^T[R_T] \alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimates</td>
<td>0.83</td>
<td>0.21</td>
<td>0.23 80 0.992 81</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Bootstrap</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>5th</td>
<td>0.76</td>
<td>0.11</td>
<td>0.09 46 0.987 74</td>
</tr>
<tr>
<td>95th</td>
<td>0.89</td>
<td>0.35</td>
<td>0.47 120 0.997 87</td>
</tr>
</tbody>
</table>
Table 4: Testing the NCC when \( \log M_T[R_T] \) depends on excess returns of variance in down and up equity markets (Model C)

In Model C, we allow for asymmetric effects of return variance on \( M_T[R_T] \), as follows:

\[
M_T[R_T] = \exp \left( m_0 - 1 + \eta_{\text{variance}}^+ 1_{R_T<1} (R_T^{\text{variance}} - R_{f,t}) + \eta_{\text{variance}}^- 1_{R_T>1} (R_T^{\text{variance}} - R_{f,t}) \right).
\]

We compute the gross return, \( R_T^{\text{variance}} \), based on the payoff of the squared log contract (i.e., \( \{\log R_T\}^2 \)), and accordingly synthesize the price of \( \{\log R_T\}^2 \) from options. Specifically,

\[
R_T^{\text{variance}} = \frac{\{\log R_T\}^2}{q_t,\{\log R_T\}^2}, \text{ where }
\]

\[
q_t,\{\log R_T\}^2 = R_T^{-1} q_t,\{\log R_T\}^2, \\
\quad = \int_{K<S_t} \frac{2(1 - \log \frac{K}{S_t})}{K^2} \text{put}_t,T[K] \ dK + \int_{K>S_t} \frac{2(1 - \log \frac{K}{S_t})}{K^2} \text{call}_t,T[K] \ dK.
\]

Reported is the unconditional correlation between \( M_T[R_T]R_T \) and \( R_T \), denoted as NCC\( _T \). SD is the standard deviation of \( M_T[R_T] \). We obtain the estimates of \((m_0, \eta_{\text{variance}}, \eta_{\text{variance}}^+)\) by solving \( \inf_{M \in M} \mathbb{E}(M \log M) \) with \( M \equiv \{ M > 0 \text{ such that } \mathbb{E}(M\{1_{R_T<1}(R_T^{\text{variance}} - R_{f,t})\}) = 0, \mathbb{E}(M\{1_{R_T>1}(R_T^{\text{variance}} - R_{f,t})\}) = 0, \mathbb{E}(M) = \mathbb{E}(R_{f,t}^{-1}) = \mu_M, \text{ and } \mathbb{E}(M \log M) < \infty \}, \) where \( \mathbb{E}(\cdot) \) is unconditional expectation. The solution is \( M^* = \exp(m_0 - 1 + (\eta_{\text{variance}}^-)^* 1_{R_T<1} (R_T^{\text{variance}} - R_{f,t}) + (\eta_{\text{variance}}^+)^* 1_{R_T>1} (R_T^{\text{variance}} - R_{f,t})) \), where \((m_0, (\eta_{\text{variance}}^-)^*, (\eta_{\text{variance}}^+)^*)\) solve \( \inf_{(m_0, \eta_{\text{variance}}, \eta_{\text{variance}}^+)} \{ -m_0 \mu_M + \mathbb{E}(\exp(m_0 - 1 + \eta_{\text{variance}}^1 R_T^{\text{variance}} - R_{f,t}) + \eta_{\text{variance}}^+ 1_{R_T>1} (R_T^{\text{variance}} - R_{f,t})) \} \). We adopt a bootstrap procedure and draw \((R_{f,t}, R_T, R_T^{\text{variance}})\) with replacement. Then, we reestimate \((m_0, \eta_{\text{variance}}, \eta_{\text{variance}}^+)\). The reported confidence intervals are based on 10,000 bootstrap samples. All reported results rely on data from the S&P 500 index options market from January 1990 to December 2018 (29 years, 348 option expiration cycles).

<table>
<thead>
<tr>
<th>Properties of ( M_T[R_T] )</th>
<th>SD (annual, %)</th>
<th>Mean (monthly)</th>
<th>Minimum (annual, %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate ( m_0 ) ( \eta_{\text{variance}} ) ( \eta_{\text{variance}}^+ ) NCC( _T )</td>
<td>1.132 0.118 0.647</td>
<td>0.12</td>
<td>250 0.998 60</td>
</tr>
<tr>
<td>Bootstrap ( 5^{th} ) ( 95^{th} )</td>
<td>1.082 0.008 0.470 0.84 179 0.998 41</td>
<td>1.233 0.267 1.111 0.21</td>
<td>343 0.998 68</td>
</tr>
</tbody>
</table>
Figure 1: Expected excess return of the market

Plotted is the expected excess return of the market (expressed in annualized percentage terms) and is computed following equation (4). The study period is January 1990 to December 2018 (348 options expiration cycles).
Figure 2: Difference between the expected excess return of the market and the lower bound

Plotted is the difference between the expected excess return of the market and the lower bound (expressed in annualized percentage terms):

\[ \{ \mathbb{E}^p(R_T) - R_{f,t} \} \frac{R_{f,t}^{-1} \operatorname{var}_t^Q(R_T)}{\text{lower bound}}. \]

The expected excess return of the market is computed following equation (4), whereas the lower bound, \( R_{f,t}^{-1} \operatorname{var}_t^Q(R_T) \), is based on Martin (2017, equation (5)). The study period is January 1990 to December 2018 (348 options expiration cycles).