ESSAYS ON INTRA-MARKET EFFICIENCY AND FINANCIAL CONTAGION

by

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ABSTRACT OF THE DISSERTATION

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The first essay of this dissertation shows that financial contagion risk is an important source of the risk premium. Intermediaries' contribution to aggregate financial contagion is estimated in a new state space framework and a tradable financial contagion portfolio is formed. More contagious intermediaries earn excess returns over less contagious ones that cannot be explained by commonly used factor models. The relative performance of contagious intermediaries is also priced in the cross section of stock returns. Stocks that comove more strongly with contagious intermediaries earn monotonically greater returns. These results are robust to factor model specification, test assets, and time period considered.

The second essay shows that exchange traded funds (ETFs) persistently trade at a premium to net asset value (NAV) and that market segmentation can explain this puzzling regularity. Tracking error standard deviation is used as the measure of market segmentation. ETFs with larger tracking error standard deviations trade at higher premiums, consistent with the notion that investors are willing to pay a premium to receive liquidity and diversification benefits from holding ETFs rather than the underlying securities directly. These results are robust to investor sentiment effects. Further tests validate that tracking error standard deviation has the desirable properties of a market segmentation measure.

The third essay shows that previous studies substantially understate the magnitudes of arbitrage profits in the closed-end fund market. The assumption that closed-end fund returns depend only on current premiums is relieved in favor of returns being dependent on an optimally chosen history of premiums. Incorporating the information content of a fund's premium innovation history substantially improves expected return estimates. In doing so, arbitrage profits are increased from an annualized 14.9 percent return with a Sharpe ratio of 1.519 to an 18.2 percent return with a Sharpe ratio of 1.918. These results are robust to a wide range of tests. They deepen the closed-end fund discount puzzle and pose a challenge to the market efficiency in these products.

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1 Introduction

Market efficiency and the effect that financial contagion has on asset prices has become of central importance to financial economists in recent years. This dissertation is comprised of three essays which look at intra-market efficiency in the financial industry, the closed-end fund (CEF) market, and the exchange traded fund (ETF) market. Here, intra-market efficiency refers to the relative pricing of securities in a specific market. Intra-market efficiency is violated when profitable arbitrage opportunities, riskless or through pairs trading, predictably persist.

The first essay of this dissertation examines how financial contagion risk affects the pricing kernel. Financial intermediaries serve a special role in the economy through investing on households' behalf and by issuing credit which both can affect the aggregate consumption possibility set. As financial intermediaries experience negative shocks, household wealth decreases and credit may be constrained. In the aggregate, consumption will be diminished. Conversely, as financial intermediaries experience positive shocks, household wealth increases and credit availability may be liberated and, in the aggregate, consumption increases. Financial intermediaries' propensity to experience positive and negative shocks contemporaneously will shock aggregate consumption possibilities in the same direction. Asset pricing theory proposes that risk-averse investors with concave utility will require a greater return on securities whose returns experience greater covariation with contagious intermediaries since these securities have high payoffs in good times and low payoffs in bad times.

Financial contagion is defined in this dissertation to be covariation in bank stock returns in excess of what is predicted by overall market movements. As an innovation to the contagion methodology literature, this paper scales excess bank return covariances by the return variance of the financial sector to give estimates of the contribution of each financial intermediary to total financial contagion as well as to provide an estimate of the fraction of the financial sector's return variance that is caused by financial contagion.

The financial contagion risk factor portfolio (HCMLC) is the arbitrage portfolio formed by buying the decile of most contagious intermediaries and selling the decile of least contagious intermediaries. This arbitrage portfolio is found to yield an annualized mean return of 6.0 percent which cannot be explained by the commonly used market, small-minus-big, the high-minus-low, momentum, and liquidity factors. Estimated annualized HCMLC risk premiums are 5.4 percent in the firm-level cross-section of CRSP stocks when the CAPM is augmented with the financial contagion factor and 3.9 percent when the FFCPS model is augmented with the HCMLC factor. Significant HCMLC risk premiums are also obtained in the cross-section of test portfolios sorted on size, book-to-market (B/M), momentum, and industry.

The second essay introduces a new ETF premium puzzle. In a frictionless market, ETF share prices will equal NAV. If this were not the case, then a riskless arbitrage opportunity would exist. To the contrary, this paper finds that ETFs persistently trade at a premium. In 89 percent of sample months, mean ETF share prices are greater than NAV. Further, mean premium half-lives range from 0.574 days for ETFs that invest in domestic equities to 8.891 days for ETFs that invest in domestic fixed income. ETFs provide a means for investors to gain access to a cash flow stream indirectly that may be inaccessible completely or only accessible at a high cost otherwise. If markets are segmented and ETFs provide liquidity benefits to investors, then rational investors should be willing to pay a premium to NAV as long as the cost of the premium is less than the liquidity and diversification benefits received. Tracking error standard deviation ($TESD$), the standard deviation of the difference between NAV returns and returns on the basket of securities that it aims to replicate, is used in this paper as the measure of market segmentation. In more segmented markets, ETF managers are expected to have less precise tracking ability.

$TESD$ is found to be positively related to premiums after controlling for fund characteristics, transaction costs, and tax overhang liabilities. Accessibility to foreign securities and fixed income securities through ETFs are revealed to be the most valuable to investors. Alternative hypotheses about premium dynamics include the contingent tax liability hypothesis and the investor sentiment hypothesis. This paper finds no evidence of a similar tax-related pattern in the ETF market. The investor sentiment and noise trading hypotheses state that irrational noise traders create a form of idiosyncratic risk that deters rational risk-averse arbitrageurs from trading. this paper finds that investor sentiment affects premium levels in the ETF market. ETF premiums are found to be a contrarian predictor of NAV returns, market returns, and returns on the small-minus-big portfolio at the three-month holding period horizon. After controlling for traditional measures of investor sentiment, $TESD$ continues to have explanatory power for ETF premiums. Further tests confirm that $TESD$ is a robust measure for market segmentation. Other studies can also benefit from using $TESD$ as a market segmentation measure where market segmentation or barriers to entry are difficult to measure.

The third essay of this dissertation shows that the mean-reversion in the CEF market can be optimally exploited to obtain larger arbitrage profits than have been previously documented in the literature. Two new conditioning models of expected returns that exploit the information content of premiums in different ways. The first, a basic mean-reversion (BMR) model, predicts future returns conditioned on current premium alone. The second model forecasts future returns in an Augmented Dickey-Fuller (denoted as RADF) type regression, further conditioning on lagged innovations in premiums. Including lagged premium innovations takes advantage of the information contained in the path of historic premiums. The trading strategy results further greatly deepen the puzzle by showing that previous studies substantially understate the level of inefficiency in the CEF market. The long-short quintile portfolio strategy, using the BMR model, yields annualized mean returns of 17.3 percent with a Sharpe ratio of 1.862. When the RADF model is used, the annualized mean long-short strategy return is 18.2 percent with a Sharpe ratio of 1.918. Since the RADF model yields substantially larger arbitrage profits than the BMR model, the traditional view that expected CEF returns are independent of the path taken by premiums is rejected.

Trading strategy returns cannot be explained by the market, size, value, momentum, or liquidity factors. The results continue to be robust when only considering subsamples of domestic funds, foreign funds, equities funds, and fixed-income funds. Returns are not driven by systematically buying foreign funds and selling domestic funds to capture a market segmentation premium or by systematically buying equities funds and selling fixed-income funds to capture the equity premium puzzle. Additionally, time period consistency of returns is tested by partitioning the out-of-sample period into two halves. Contrary to what is expected in efficient markets with rational learning, there is no statistically significant difference between mean returns in the first half of the out-of-sample period and mean returns in the second half of the out-of-sample period.

2 Financial Contagion and the Stochastic Discount Factor

Financial intermediaries serve a special role in the economy through investing on households' behalf and by issuing credit which both can affect the aggregate consumption possibility set. As financial intermediaries experience negative shocks, household wealth decreases (Allen, Bali, and Tang (2012)) and credit may be constrained (Duchin, Ozbas, and Sensoy (2012) and Ivashina and Scharfstein (2010)). In the aggregate, consumption will be diminished. Conversely, as financial intermediaries experience positive shocks, household wealth increases and credit availability may be liberated and, in the aggregate, consumption increases. Financial intermediaries' propensity to experience positive and negative shocks contemporaneously will shock aggregate consumption possibilities in the same direction. Asset pricing theory proposes that risk-averse investors with concave utility will require a greater return on securities whose returns experience greater covariation with contagious intermediaries since these securities have high payoffs in good times and low payoffs in bad times.

Alternatively, since intermediaries serve as agents of households to invest on their behalf, it could be that intermediaries' marginal utility of wealth and stochastic discount factor (SDF) prices securities as proposed in the Cochrane (2011) presidential address. In the case of an intermediary SDF, increased financial contagion leads to increased interbank funding illiquidity, such as observed in Schnabl (2012). A severe enough decrease in funding liquidity can result in market freezes (Acharya, Gale, and Yorulmazer (2011)) or fire sales (Jotikasthira, Lundblad, and Ramadorai (2012) and Shleifer and Vishny (1992)). In each of these cases, for an intermediary with concave utility, asset payoffs will covary negatively with the intermediary's marginal utility of wealth. It follows that with an intermediary SDF, intermediaries will also require a greater expected return for holding securities that experience greater covariation with more contagious intermediaries.

This paper contributes to the new and growing area of financial intermediary asset pricing by showing that financial contagion risk enters the SDF. Financial contagion is defined in this paper as in Bekaert, et al. (2005) to be excess covariation in bank stock returns in excess of what is predicted by overall market movements. Excess bank return covariances are scaled by the return variance of the financial sector to give estimates of the contribution of each financial intermediary to total financial contagion as well as to provide an estimate of the fraction of the financial sector's return variance that is caused by financial contagion. High contagion intermediaries are found to outperform low contagion intermediaries, by an annualized mean return of 6.0 percent. Formal factor regressions show that the mean annualized abnormal return of the high contagion minus low contagion intermediary portfolio is 3.9 percent and persists after accounting for the three Fama and French (1993) factors, the Pástor and Stambaugh (2003) liquidity factor, and the Carhart (1997) momentum factor (hereafter, referred to as the FFCPS model). Additionally, a monotonic relationship cannot be rejected between intermediary portfolio contagion and intermediary portfolio mean return. Trend tests indicate that an increase in mean return of 80 basis points is required for investors to hold an adjacent intermediary decile with higher contagion risk.

The financial contagion risk factor portfolio (HCMLC) is formed by buying the decile of intermediary stocks that contribute the most to financial contagion and selling the decile of intermediary stocks that contribute the least to financial contagion. A monotonic relation between financial contagion beta and mean returns cannot be rejected. Investors require an increase in expected return of 40 basis points to hold an adjacent common stock decile with a higher financial contagion beta.

Asset pricing tests are used to test if financial contagion risk is priced in the cross section of stock returns. The price of the HCMLC factor is tested out of sample in the cross-section of firm level stock returns and test portfolios using the two-pass regression procedure of Fama and MacBeth (1973). Estimated annualized HCMLC risk premiums from Fama-MacBeth regressions are 5.4 percent in the cross-section of CRSP stocks when the CAPM is augmented with the financial contagion factor and 3.9 percent when the FFCPS model is augmented with the HCMLC factor. Significant HCMLC risk premiums are also obtained from Fama-MacBeth regressions using test portfolios sorted on size, book-to-market (B/M), momentum, and industry. Estimated Financial contagion risk premiums using these test portfolios generally range from 5 percent to 15 percent. Risk premium results are robust at the firm level and portfolio level to beta estimation window as well as time period considered in the Fama-MacBeth regressions. Pricing error tests further show that the HCMLC factor is at least as successful at pricing portfolios out of sample as the other factor models are and performs better than the CAPM and FF3F models at pricing the 49 industry portfolios, the 10 B/M portfolios, and the 25 size-B/M plus 10 momentum portfolios. This out of sample pricing performance indicates that financial contagion risk is an important source of the risk premium. As a second test for risk-premiums, ex-post cross-sectional tests are used. Significant improvement in model fit is achieved by including the HCMLC factor. Whereas the FFCPS model obtains an adjusted R^2 of 0.665 in modeling sample mean returns of the ten size portfolios, including the HCMLC factor increases the adjusted R^2 to 0.889.

The two papers that are most similar to this one are Adrian, Etula, and Muir (2012) and He and Krishnamurthy (2013). He and Krishnamurthy (2013) provides a theoretical basis for a financial intermediary SDF. Adrian, et al. (2012) empirically tests for an intermediary SDF. They find that a single-factor model, using broker-dealer leverage as the only factor, prices portfolios sorted on size, B/M, and momentum better than the Carhart four-factor model. The results in this paper provide evidence of an alternative and important avenue through which financial intermediary risk enters the SDF. While Adrian, et al. focus on intermediary leverage as a proxy for intermediary SDF, this paper focuses on how financial contagion risk enters the SDF. The intermediary-based factor in this paper has the advantage that it can be observed at any frequency while intermediary leverage observations are restricted to the quarterly frequency. This paper further adds to this literature by allowing financial intermediary returns to directly enter the SDF. Intermediary leverage and intermediary contagion need not be mutually exclusive, however. In the models of Allen and Gale (2000) and Leitner (2005), financial contagion results when interbank defaults occur in the presence of sufficiently high interbank leverage. On the other hand, financial contagion need not be correlated with intermediary leverage levels. Kyle and Xiong (2001) and Kodres and Pritsker (2002) develop models in which contagion can arise from a "flight to quality" by investors. Benmelech and Bergmann (2007) use the airline industry as a laboratory to show that contagion can alternatively arise from collateral values decreasing and increasing the cost of external finance for all participants in the industry. This paper adds to this literature financial contagion by showing that asset prices are importantly affected by contagion risks.

The remainder of this paper is organized as follows. Section 1 discusses the methodology used to estimate financial contagion. Section 2 discusses the data. Section 3 presents financial contagion estimates. Section 4 and section 5 present the main asset pricing results. Section 6 presents robustness tests. Section 7 contains concluding remarks.

2.1 Financial Contagion Methodology

Throughout this paper, the terms "bank", "financial intermediary", and "financial institution" are used interchangeably to mean the same thing. Financial contagion is defined to be the covariance term in the variance of the financial intermediary portfolio returns in excess of what is predicted by market movements. Identifying financial contagion is a three step procedure. In the first step, the component of observed bank returns that is generated by common market risk exposure is removed. Let there be N stocks that make up the bank portfolio and assume that stock returns are generated by the following k-factor model

$$r_{i,t} = \alpha_{i,t} + \boldsymbol{f}'_t \boldsymbol{\beta}_{i,t} + e_{i,t}, \qquad i \in \{1, 2, \ldots, N\}, \qquad t \in \{1, 2, \ldots, T_i\} \tag{2.1}$$

$$\boldsymbol{\beta}_{i,t} = \boldsymbol{\beta}_{i,t-1} + \boldsymbol{\eta}_{i,t} \tag{2.2}$$

where $r_{i,t}$ is the observed stock return at time t for bank i, $\boldsymbol{f}_t = (f_1, f_2, \ldots, f_k)'_t$ is a vector of observed factors at time t, $\boldsymbol{\beta}_{i,t} = (\beta_{i,1}, \beta_{i,2}, \ldots, \beta_{i,k})'_t$ is the time varying vector of k factor loadings, and $\alpha_{i,t}$ is a time-varying intercept term. $e_{i,t}$ is the bank-specific shock, which is orthogonal to the factors and is distributed $e_{i,t} \sim N\left(0, \sigma^2_{i,t}\right)$. The covariance matrix of residuals across financial institutions may not be diagonal. Non-diagonal elements that are not equal to zero represent contagious bank covariances. Equation (2.1), as it is written, allows the model parameter values to change over time. The transition equation of betas is given in eqn. (2.2). $\boldsymbol{\eta}_{i,t}$ is a vector of coefficient innovations with $e_{i,t}$ and $\boldsymbol{\eta}_{i,t}$ being uncorrelated. $\boldsymbol{\Sigma}_{i,\eta}$ is a $(k \times k)$ diagonal matrix containing the coefficient innovation variances. Using a diagonal matrix for $\boldsymbol{\Sigma}_{i,\eta}$ imposes that factor loadings follow a random walk. If $\boldsymbol{\Sigma}_{i,\eta} = \mathbf{0}$, then factor loadings are constant. The Kalman filter is used to recursively estimate the time varying regression coefficients. A detailed explanation of the Kalman filtering methodology can be found in Appendix A and Appendix B. Daily data is used to estimate eqns. (2.1) and (2.2) to capture within-month variation in factor loadings which Patton and Ramadorai (2013) show is important for modeling high-frequency risk exposure. Bank-specific shocks are the residual terms from eqn. (2.1)

$$\widehat{e}_{i,t} = r_{i,t} - \mathbf{E}\left(r_{i,t} | \mathcal{F}_{t-1}\right) = r_{i,t} - \widehat{\alpha}_{i,t|t-1} - \boldsymbol{f}_t' \widehat{\boldsymbol{\beta}}_{i,t|t-1} \tag{2.3}$$

where $\mathbf{E}\left(\cdot\right)$ is the mathematical expectations operator and $\mathcal{F}_{t-1}$ is the information set available at time $t-1$.

In the second step, the estimated residuals from eqn. (2.3) are regressed, without an intercept term, on returns of the value-weighted bank portfolio

$$\widehat{e}_{i,t} = z_{i,t} r_{I,t}^{(i)} + u_{i,t} \tag{2.4}$$

$$z_{i,t} = z_{i,t-1} + \omega_{i,t} \tag{2.5}$$

where $r_{I,t}^{(i)}$ is the return on the bank portfolio at time t. Bank i's return contribution to the total bank portfolio return must be excluded to prevent bank i's idiosyncratic shock variance from being identified erroneously as financial contagion. $z_{i,t}$ is the scalar regression coefficient at time t for bank i. The $z_{i,t}$ coefficients are restricted to vary with time following a random walk and innovation $\omega_{i,t} \sim N\left(0, \Sigma_{i,\omega}\right)$. If $\Sigma_{i,\omega} = 0$, then $z_{i,t}$ is constant across time. $z_{i,t}$ is allowed to be time varying to capture time varying financial contagion risk. $u_{i,t}$ is a random error term orthogonal to $\omega_{i,t}$ distributed as $u_{i,t} \sim N\left(\sigma_{u_i}^2\right)$.

From eqn. (2.4) it is not possible to distinguish between causality leading from the bank portfolio to the bank-specific shock of bank i, from causality leading from bank i's idiosyncratic shock to the portfolio. Unbiased covariation is sufficient for this study and knowing direction of causality is not needed. The Kalman filtering methodology is used to estimate eqn. (2.4) equation-by-equation for all banks included in the sample. Resulting time-varying coefficients in eqn. (2.4) are filtered estimates of $z_{i,t}$, $\widehat{z}_{i,t|t}$, conditional on time t information. Since $\widehat{e}_{i,t}$ is dependent on the coefficient estimates from eqn. (2.1), which are estimated with error, $\widehat{e}_{i,t}$ will contain measurement error. This measurement error will inflate the standard errors of $\widehat{z}_{i,t|t}$, but $\widehat{z}_{i,t|t}$ will continue to be an unbiased estimator of $z_{i,t}$. Unbiasedness is the only property required for this methodology.

The third step aggregates coefficient estimates from eqn. (2.4) across banks at each date. Since eqn. (2.4) is a linear model, the projection theorem shows that the estimator of $\widehat{z}_{i,t|t}$ is

$$\widehat{z}_{i,t|t} = \frac{\mathbf{E}\left(\widehat{e}_{i,t} r_{I,t}^{(i)} | \mathcal{F}_t\right)}{\mathbf{E}\left(\left(r_{I,t}^{(i)}\right)^2 | \mathcal{F}_t\right)}$$

$\mathbf{E}\left(\left(r_{I,t}^{(i)}\right)^2 | \mathcal{F}_t\right) = \sigma^2_{r_{I,t}^{(i)}}$ is the variance of bank portfolio returns at time t. Since $r_{I,t}^{(i)} = \sum_{j \neq i} w_{j,t} r_{j,t} = \sum_{j \neq i} w_{j,t}\left(\alpha_{j,t} + \boldsymbol{f}'_t \boldsymbol{\beta}_{j,t} + e_{j,t}\right)$ and the properties, $\mathbf{E}\left(\widehat{e}_{i,t} f_{l,t}\right) = 0$ for all i and $l \in [1,k]$, and $\mathbf{E}\left(\widehat{e}_{i,t}\alpha_{j,t}\right) = 0 \; \forall i,j$, it follows that

$$\widehat{z}_{i,t|t} = \frac{\sum_{j \neq i} w_{j,t} \mathbf{E}\left(\widehat{e}_{i,t} e_{j,t}\right)}{\sigma^2_{r_I^{(i)},t}} \tag{2.6}$$

w_j is the value weighting of bank j in the bank portfolio. $\alpha_{j,t}$, $\boldsymbol{\beta}_{j,t}$, and $e_{j,t}$ are the true intercept, true factor loadings, and true firm-specific shock for stock j at time t. Since $\mathbf{plim}\widehat{e}_{i,t} = e_{i,t}$ and $\mathbf{E}\left(e_{i,t}\right) = 0 \; \forall i, t$, $\mathbf{E}\left(\widehat{e}_{i,t} e_{j,t}\right)$ is an estimate of the covariance between $e_{i,t}$ and $e_{j,t}$, $\widehat{\mathbf{CV}}\left(e_{i,t}, e_{j,t}\right)$. Note that the i'th bank's contribution to the portfolio's return is held out in eqn. (2.4) causing $r_{I,t}^{(i)}$ to vary for a given time t depending on which bank is the dependent variable. If, for all i, the $\widehat{z}_{i,t|t}$ estimates had common denominators, the fraction of portfolio variance due to contagion could be estimated by taking the weighted summation $\sum_i w_{i,t}\widehat{z}_{i,t|t}$. However, since $r_{I,t}^{(i)}$ is different for each i, each $\sigma^2_{r_I^{(i)},t}$ will also be different. Therefore, $\widehat{z}_{i,t|t}$ must be post-multiplied by the variance ratio $\sigma^2_{r_I^{(i)},t}\left(\sigma^2_{r_I,t}\right)^{-1}$ prior to the summation. $\sigma^2_{r_I,t}$ is the bank portfolio return variance, including all banks. Since $\sigma^2_{r_I^{(i)},t}$ and $\sigma^2_{r_I,t}$ are unobservable and must be estimated, the following parsimonious 90-day rolling historical variance estimators are used

$$\widehat{\sigma}^2_{r_I^{(i)},t} = \frac{1}{89}\sum_{k=t-90}^{t-1}\left(r_{I,k}^{(i)} - \widehat{\mu}_{r_I^{(i)},t}\right)^2 \tag{2.7a}$$

$$\widehat{\mu}_{r_I^{(i)},t} = \frac{1}{90}\sum_{k=t-90}^{t-1} r_{I,k}^{(i)} \tag{2.7b}$$

$$\widehat{\sigma}^2_{r_I,t} = \frac{1}{89}\sum_{t-90}^{t-1}\left(r_{I,k} - \widehat{\mu}_{r_I,t}\right)^2 \tag{2.7c}$$

$$\widehat{\mu}_{r_I,t} = \frac{1}{90}\sum_{k=t-90}^{t-1} r_{I,k} \tag{2.7d}$$

where $r_{I,t}$ is the return on the complete bank portfolio (all bank stock returns included), $\widehat{\mu}_{r_I^{(i)},t}$ is the mean return estimator for the hold out bank portfolio for the trailing 90 days, and $\widehat{\mu}_{r_I,t}$ is the mean return estimator for the complete bank portfolio for the trailing 90 days. A variance estimator using trailing observations is used rather than a centered variance estimator so that variances can be estimated with an investor's current information set. Admittedly, eqns. (2.7a)-(2.7d) are simple variance estimators. Since the ratio of variances is used, which is approximately equal to one, using a more sophisticated variance estimator will increase complexity while only adding marginal additional value.

Summing the product $w_{i,t}\widehat{z}_{i,t|t}\widehat{\sigma}^2_{r_I^{(i)},t}\left(\widehat{\sigma}^2_{r_I,t}\right)^{-1}$ over all i at each time t yields

$$
\begin{aligned}
FC_t &= \sum_i w_{i,t}\widehat{z}_{i,t|t}\widehat{\sigma}^2_{r_I^{(i)},t}\left(\widehat{\sigma}^2_{r_I,t}\right)^{-1} \\
FC_t &= \sum_i FC_t^{(i)} = \frac{2\sum_{i,j:i<j} w_{i,t}w_{j,t}\widehat{\mathbf{CV}}\left(e_{i,t},e_{j,t}\right)}{\widehat{\sigma}^2_{r_I,t}} \\
FC_t &= \frac{C}{A+B+C} \\
A &= \sum_{l=1}^{k}\widehat{\mathbf{V}}\left(f_{l,t}\right)\left(\sum_i\left(w_{i,t}\beta_{i,l,t}\right)^2 + 2\sum_{i,j:i<j} w_{i,t}w_{j,t}\beta_{i,l,t}\beta_{j,l,t}\right) \\
B &= \sum_i w_{i,t}^2\widehat{\mathbf{V}}\left(e_{i,t}\right) \\
C &= 2\sum_{i,j:i<j} w_{i,t}w_{j,t}\widehat{\mathbf{CV}}\left(e_{i,t},e_{j,t}\right)
\end{aligned}
\tag{2.8}
$$

Eqn. (2.8) shows that at each time t FC_t is an estimator of the fraction of bank portfolio return variance that is due to the covariances in bank-specific shocks, or financial contagion. Since FC_t is a ratio, it will be bounded between -1 and +1. The first term in the denominator of eqn. (2.8), A, is the contribution of common fundamental risks to the variance of the bank portfolio's return variance. If the entire variation of bank returns can be explained by the factor model, then $FC_t = 0$. The second term of the denominator, B, is the contribution that banks' idiosyncratic risks contribute to the overall bank portfolio's return variance. The third term in the denominator, C, is the effect that financial contagion has on the bank portfolio's return variance. FC_t will only be non-zero if C is non-zero.

In the empirical results that follow, eqn. (2.1) is estimated with the Kalman filter within the market model framework presented below

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}r_{m,t} + e_{i,t} \tag{2.9}$$

where $r_{m,t}$ is the daily return on the market portfolio. Since other factors have little additional explanatory power at the daily frequency, using the market return as the only factor keeps the model parsimonious without a loss of generality. The residuals from the market model are then used as the dependent variable in eqn. (2.4) and eqn. (2.4) is estimated with the Kalman filter.

2.2 Data and Summary Statistics

Daily bank stock prices from January 1, 1960 to December 31, 2012 are obtained from the CRSP daily stock file. All domestic banks (SIC codes from 6000 to 6199 and share code 10 or 11) and broker/dealers (SIC codes from 6200 to 6299 and share code 10 or 11) are initially included in the sample when their stock price first falls within a share price of \$5 and \$1,000. To avoid survivorship bias, once a financial stock enters the sample it remains in the sample, regardless of share price. Financial stocks are dropped from the sample, if and when they are dropped from CRSP. There are 2,388 banks in the sample with a total of 5,953,497 daily bank stock observations.

For asset pricing tests, all common stocks (CRSP share code 10 or 11) within the CRSP universe are collected at a monthly frequency from January 1968 to December 2011 from the CRSP monthly stock file. A stock enters the sample once it has a share price greater than \$5 and less than \$1,000. Once a stock enters the sample it remains in the sample, regardless of share price. It is removed from the sample if and when it is removed from CRSP to avoid survivorship bias. Daily financial stock returns are aggregated to monthly returns by converting daily returns into log returns, summing each month's log returns, and then converting the monthly aggregated log returns back into arithmetic returns by taking the exponential function of the aggregated log returns. Factor data is obtained for the same period at a monthly frequency from two sources. Fama and French's three factors, as well as the momentum factor, are obtained from Kenneth French's website and the tradable liquidity factor is obtained from Ľuboš Pástor's website. Asset pricing tests are constrained to the January 1968 to December 2011 period since that is the range of dates for which the tradable Pástor and Stambaugh liquidity factor portfolio is available.

Figure 2.1 plots the time series of the number of financial stocks that are contemporaneously included in the sample. Sample size increases from 10 financial institutions in 1960 to approximately 1,000 in 1999. Thereafter, the sample size decreases to approximately 500 banks in 2012. Summary statistics for the sample of financial institutions and for estimated financial contagion are presented in panel A of Table 2.1. Mean bank market value of equity (MVE) is \$1.42 billion with a standard deviation of \$8.91 billion. Median bank size is \$0.08 billion, providing evidence that the distribution of bank size is heavily skewed to the right. Banks' contributions to financial contagion, $FC_t^{(i)}$, are also heavily skewed to the right. Whereas the maximum contribution to financial contagion is 3.9 basis points, the first and third quartiles are 0.0 and 0.8 basis points, respectively. The sample mean fraction of observed bank portfolio return variance caused by financial contagion, FC_t, is 17.9 percent and it has a sample standard deviation of 3.5 percent. FC_t obtains a maximum of 27.5 percent and a minimum of 8.9 percent. Panel B presents summary statistics of the stock and factor return sample. Mean stock price is \$24.81, mean MVE is \$1.22 billion, and mean monthly trading volume is 6.7 million shares. Mean annualized returns on the MRKT, SMB, HML, MOM, LIQ and HCMLC portfolios are 6.0 percent, 1.2 percent, 4.8 percent, 9.6 percent, 6.0 percent, and 7.2 percent.

Figure 2.2 plots the level of the value-weighted bank index in the top panel, bank index return variance in the middle panel, and aggregate bank firm-specific shock covariances in the bottom panel. January 1, 1960 is used as the base year for index level and the base index level is set equal to one. Estimated bank-specific shock covariances display a countercyclical nature. Covariances are high in periods of market stress and close to zero in times of relative market tranquility. During the 2007-'09 financial crises, covariances between bank stocks unexplainable by market risk increased dramatically.

2.3 Financial Contagion Estimates

Figure 2.3 plots FC_t estimates obtained from eqn. (2.8), the fraction of bank index return variance that is caused by financial contagion on a given day. Graphically, FC_t

scales the covariances in the bottom panel of Figure 2.2 by the variances in the middle panel of Figure 2.2. Financial contagion is generally in the range of 11 percent to 16 percent from 1960 to 1985. From 1985 to 2001 the level of financial contagion increases from 12.5 percent to 27 percent. During the 2007-2009 financial crises, FC_t experienced dramatic changes in levels.

Figure 2.4 plots financial contagion, annotated with key corporate and policy events that occurred during the crisis period. The events included are: the failure of Bear Stearns, the emergency SEC naked short selling ban on a number of financial institutions, Lehman Brothers filing for chapter 11 bankruptcy protection, the bailout of American International Group (AIG), the passing of the Emergency Stabilization Act of 2008 into law by congress, the announcement of the troubled asset relief program (TARP), the announcement of the term asset-backed loan facility (TALF), the announcement of U.S. government subsidization of Bank of America, and the "Six Months of TARP" report. These events were chosen since they correspond most closely with sharp changes in financial contagion[1].

Bear Stearns failing on March 14, 2008 was the first sign that financial institutions were in trouble. However, FC_t increased only slightly on the news. Contagion rose less than 100 basis points on the news. A much larger revision to financial contagion occurred on July 15, 2008 when the SEC made an emergency order to ban naked short selling on a number of financial institutions that were perceived to pose a systemic risk. Financial contagion increased from 19.2 percent to 23.4 percent. This is the time that contagion was at its greatest during the crisis period. Lehman Brothers filed for chapter 11 bankruptcy protection on September 15, 2008. AIG received an $85 billion credit facility from the Federal Reserve the following day, on September 16, 2008. On October 3, 2008 the Emergency Stabilization Act of 2008 was passed by congress. This bill, which contained the troubled asset relief program (TARP), authorized the U.S. Treasury to spend up to $700 billion to unfreeze credit markets. TARP was formally announced to the public on

[1] A more detailed timeline of the financial crisis can be seen on the St. Louis Federal Reserve's website.

October 14, 2008. Market perceptions of financial contagion were dramatically impacted by these events. From September 16, 2008 to mid November 2008, financial contagion dropped from 21 percent to 9 percent. At this point, financial contagion expectations were at one of their lowest over the fifty-two year sample period.

Since the Lehman Brothers and AIG events are only separated by one day it is difficult to empirically identify which event was the primary source of the large reduction in contagion risk that followed. An argument in favor of the Lehman Brothers event could be that banks reduced their leverage, as is found in Adrian and Song (2014) (Figure 5, page 383), fearing that there would be no backstop by the government. Conversely, an argument in favor of the AIG event could be that traders viewed the government as having set up a backstop for systemically important institutions and as a result traders priced a lower contagion risk into the market.

Financial contagion sharply increased in the second half of November 2008, however, rising from the low of 9 percent to 13 percent. The term asset-backed securities loan facility (TALF) was announced on November 25, 2008 to support the issuance of asset-backed securities (ABS). Contagion fell mildly following this, until it increased sharply again in response to the January 16, 2009 announcement that the government would provide a package of guarantees, liquidity, and capital to Bank of America. From January 16, 2009 to February 2009, financial contagion increased from 13 percent to 19 percent. Market expectations of financial contagion risks were revised higher in response of the government's intervention. The last sharp increase in contagion perceptions occurred in response to the "Six Months of TARP" report on April 7, 2009. Intermediary contagion subsequently increased from 18 percent to 20 percent.

2.4 Financial Contagion Risk and Returns

2.4.1 Financial Contagion Risk and Bank Returns

Each month financial stocks are sorted into equally-weighted portfolios based on their previous month's average contribution to aggregate financial contagion, $(T_m)^{-1} \sum_{t=1}^{T_m} FC_t^{(i)}$.

T_m denotes the number of trading days in the month. Portfolio returns are observed the following month and then portfolios are re-sorted. Bank returns are trimmed at the 2.5 percent and the 97.5 percent levels prior to portfolio formation to mitigate the influence of extreme returns. Results are unchanged when bank returns are only trimmed at the 99 percent level. Equally-weighted contagion-sorted financial portfolios are used rather than value-weighted contagion-sorted financial portfolios in this paper since value-weighting the financial portfolios would lead to highly skewed portfolio holdings.

Table 2.2 presents return statistics for contagion sorted bank portfolios. Panel A presents mean returns, their Sharpe ratios, and mean market value of equity of stocks in each portfolio. Decile, quintile, and tercile sorting methods are presented for robustness. Mean annualized returns for the decile, quintile, and tercile of financial stocks most susceptible to financial contagion are 11.9 percent, 12.2 percent, and 11.2 percent, respectively. Mean annualized returns for the least contagious portfolios are 5.9 percent, 5.3 percent, and 5.5 percent, respectively. The differences between the high contagion portfolios and low contagion financial stock portfolios are 6.0 percent, 6.9 percent, and 5.7 percent for decile sorts, quintile sorts, and tercile sorts, respectively. Returns are significantly different from zero at the one percent level or better for each sorting method. This relative outperformance of the high contagion portfolio is indicative that investors holding more contagious banks require higher expected returns.

Figure 2.5 plots the log wealth process of a trading strategy, rebalanced monthly, that buys the highest contagion decile and sells the lowest contagion decile, denoted as the HCMLC portfolio. Log wealth processes of the excess market (MRKT), small-minus-big (SMB), high B/M minus low B/M (HML), momentum (MOM), and tradable liquidity (LIQ) portfolios are also plotted. \$1.00, initially invested in the HCMLC bank portfolio in January, 1968, grows to \$8.48 dollars by December, 2011. Over the same period, \$1.00 in the MRKT, SMB, HML, MOM, and LIQ portfolios grows to \$5.35, \$2.00, \$5.96, \$23.79, and \$9.28, respectively.

Annualized Sharpe ratios for the long-short contagion portfolios are 0.430, 0.588, and 0.589 for decile, quintile and tercile sorts, respectively. These Sharpe ratios are roughly in line with the market Sharpe ratio of 0.560 (not reported) over the same period. The least contagious quintile of financial stocks has a negative Sharpe ratio because the annualized mean risk-free rate during the sample period was 5.319 percent. Mean MVE of financial stocks included in each portfolio are presented in the final column. Financial institutions in the most contagious portfolios are larger than those in the least contagious ones. Mean MVE in the most contagious portfolios are $8.303, $4.490, and $2.788 billion for decile sorts, quintile sorts, and tercile sorts, respectively. Mean market caps in the least contagious portfolios are $0.273, $0.155, and $0.106 billion for decile sorts, quintile sorts, and tercile sorts, respectively.

Panel B of Table 2.2 presents regression results from regressing financial contagion sorted bank portfolio excess returns on the Carhart (1997) 4-factor model, augmented with the Pástor and Stambaugh (2003) tradable liquidity factor (hereafter, referred to as the FFCPS model). Long-short contagion portfolio return alphas for decile, quintile, and tercile sorts are 3.9 percent, 4.5 percent, and 3.2 percent, respectively. Alphas from each of the sorting methods are significant at the five percent level or better. These significant alphas appear to be driven by the underperformance of the least contagious portfolios. Whereas abnormal returns are insignificantly different from zero for the most contagious portfolios, abnormal returns for the least contagious portfolios are -3.0 percent, -3.5 percent, and -3.4 percent for decile, quintile, and tercile sorts, respectively. Negative alphas for the least contagious portfolios are each significant at the five percent level or better. Long-short contagion portfolio returns obtain a heavily positive loading on the market factor, a negative loading on the SMB factor, and a positive loading on the HML factor. There is not a significant factor loading on the MOM or LIQ factors.

Table 2.3 presents bank portfolio returns for each decile sorted on financial contagion risk and tests for monotonicity of trend in portfolio returns. If financial contagion risk enters the SDF, then a monotonic trend should be observed between contagion risk decile and decile mean return. Panel A contains mean contagion portfolio returns in the first two rows and portfolio return alphas obtained from regressing returns on the FFCPS model in the final two rows. Mean portfolio returns generally trend higher from the least contagious portfolio to the most contagious portfolio. The least contagious intermediary portfolio has an expected return of 5.9 percent and the portfolio of most contagious intermediaries has an expected return of 11.9 percent. The difference between the two returns is significant at the one percent level. Portfolio return alphas display an upward trend as well. Annualized alphas for the least contagious bank portfolio and most contagious bank portfolio are -3.0 percent and 1.0 percent, respectively. The difference between the two alphas is statistically significant. The significant negative alphas of the three least contagious deciles shows that these banks are persistently overpriced since they serve as a hedge against contagion risk.

Panel B formally tests for monotonicity of trend in portfolio mean returns and alphas. Due to random sampling error, a purely monotonic trend is unlikely to be observed in practice. Two tests for monotonicity, one parametric and one non-parametric, are used to test if the null that there is no monotonic relationship between intermediary portfolio contagion risk and portfolio mean return can be rejected. The parametric test regresses mean portfolio returns and alphas, separately, on a constant and trend variable ranging from one to ten. This regression test has the convenient property of providing evidence as to how much additional expected return investors require to hold an adjacently more contagious portfolio of financial intermediaries. Kendall's tau measure of rank correlation is the non-parametric test[2]. Kendall's tau is a measure of similarity in decile ranking and mean return ranking. If the two rankings are sufficiently similar, then the null hypothesis of no monotonic relationship between portfolio financial contagion risk and portfolio mean returns is rejected. Monotonicity tests, using the regression test, are presented in columns one and two, for mean returns and alphas, respectively. Tests using Kendall's tau are presented in columns three and four for mean returns and alphas, respectively. Both tests reject the null hypothesis of no monotonic relationship at the one percent level for both portfolio mean returns and alphas. The trend coefficient in the regression test indicates that investors require an increase in expected return of 80 basis points to hold

[2] The interested reader is referred to Kendall (1938) for details on the test computation.

an adjacently more contagious portfolio of financial institutions.

2.4.2 Financial Contagion Risk and Stock Returns

Stocks' exposure to financial contagion risk is estimated with the following univariate and multivariate regressions

$$r^e_{i,t} = \beta_{i,0} + \beta_{i,MRKT} r_{MRKT,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t} \tag{2.10}$$

$$\begin{aligned} r^e_{i,t} = \beta_{i,0} &+ \beta_{i,MRKT} r_{MRKT,t} + \beta_{i,SMB} r_{SMB,t} + \beta_{i,HML} r_{HML,t} \\ &+ \beta_{i,MOM} r_{MOM,t} + \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t} \end{aligned} \tag{2.11}$$

$r^e_{i,t}$ is the excess return on stock i, $r_{MRKT,t}$ is the excess return on the market portfolio (MRKT), $r_{SMB,t}$ is the return on the small-minus-big portfolio (SMB), $r_{HML,t}$ is the return on the high B/M-minus-low B/M portfolio (HML), $r_{MOM,t}$ is the return on the winners-minus-losers momentum portfolio (MOM), $r_{LIQ,t}$ is the return on the portfolio of stocks with highest liquidity beta minus the portfolio of stocks with lowest liquidity beta (LIQ), and $r_{HCMLC,t}$ is the return on the decile of most contagious bank stocks minus the return on the decile of least contagious bank stocks, denoted the HCMLC portfolio. Asset pricing results are unchanged if the HCMLC portfolio is formed using quintile or tercile sorts. Eqns. (2.10) and (2.11) are estimated in a rolling regression framework, using 60-months of return observations. Stocks are sorted into value-weighted deciles based on their time t HCMLC beta and then portfolio returns are observed in time $t+1$.

Table 2.4 presents the correlation matrix of factor portfolio returns. Correlations between returns on the HCMLC portfolio, returns on the VIX (VIX), and changes in aggregate corporate default risk (DEF, defined as the log change in the log difference between yields on Baa and Aaa rated bonds) are included to test if the HCMLC portfolio simply captures changing aggreagate volatility risk or changing aggregate default risk. HCMLC returns are most correlated with the MRKT portfolio at 0.49 and least correlated with the SMB portfolio at -0.15. The correlations between HCMLC and DEF and between HCMLC and VIX are 0.111 and -0.344, respectively. These low correlation magnitudes indicate that financial contagion risk is a separate risk from aggregate volatility risk and aggregate default risk. HCMLC's correlations with the other factors are negative and close to zero.

Table 2.5 presents returns from HCMLC beta sorted stock portfolio returns. Stock portfolio returns sorted on financial contagion beta from the univariate regression in eqn. (2.10) and their t-statistics are presented in the first two rows of Panel A. The lowest decile has an annualized mean return of 3.3 percent and the highest decile earns a mean return of 7.1 percent. The difference is not statistically significant. Generally, there is a positive relationship between contagion beta and expected return. Panel B presents the results from regressing portfolio mean returns on a constant and trend variable extending from one to ten to test the null hypothesis of no monotonic trend in portfolio mean returns. Results of this test are presented in column one. The null is rejected in favor of portfolios with greater financial contagion beta requiring a higher expected return. The regression trend coefficient indicates that investors require an additional 40 basis points in expected return to hold an adjacent portfolio with greater financial contagion beta. Kendall's tau in column three of Panel B agrees with the regression trend test. The monotonicity tests provide evidence that the difference in mean returns between the highest and lowest contagion beta deciles results from sampling error in the extreme portfolios.

Mean portfolio returns and t-statistics for portfolios sorted on financial contagion betas obtained from the multivariate regression in eqn. (2.11) are presented in the final two rows of Panel A. Similar to the univariate case, there is generally a positive relationship between contagion beta and expected returns. The lowest decile has a mean return of 5.3 percent and the highest decile has a mean return of 6.9 percent. Both the regression trend test and Kendall's tau reject the null hypothesis of no monotonic relationship between mean portfolio return and financial contagion beta at the five percent level or better. Again, the regression trend test indicates that investors require an additional 40 basis points in expected return to hold an adjacent stock portfolio with greater financial contagion beta. Sampling error in the two extreme portfolios causes the difference to be insignificant, similarly to the univariate case.

Figure 2.6 plots the wealth processes of investing in portfolios sorted on betas obtained from eqn. (2.11). Stocks are sorted into value-weighted terciles to reduce the effect of sampling error in the extreme deciles mentioned above. Portfolios are formed by buying the tercile with greatest factor beta and selling the tercile with lowest factor beta and rebalanced monthly. Five years of observations are lost in acquiring the first beta estimates. The active strategy of investing in the HCMLC beta sorted long-short portfolio outperforms each of the other long-short portfolios sorted on the other factor betas. $1.00 invested in January 1973 in the HCMLC beta sorted long-short portfolio becomes $3.99 in October, 2011 with a Sharpe ratio of 0.43 (not reported). $1.00 invested in the MRKT, SMB, HML, MOM, and LIQ beta sorted long-short portfolios become $0.48, $2.33, $2.52, $1.25, and $0.61, respectively. Sharpe ratios (not reported) of the MRKT, SMB, HML, MOM, and LIQ beta sorted long-short portfolios are -0.13, 0.24, 0.26, 0.11, and -0.06, respectively.

2.5 Financial Contagion Risk and the SDF

Financial contagion risk is proposed to enter a linear SDF, m_t, given by

$$0 = \mathbf{E}\left(m_{t+1} r^e_{i,t+1}\right) \tag{2.12}$$

$$\begin{aligned} m_t = & \ 1 - b_1 r_{MRKT,t} - b_2 r_{SMB,t} - b_3 r_{HML,t} \\ & - b_4 r_{MOM,t} - b_5 r_{LIQ,t} - b_6 r_{HCMLC,t} \end{aligned} \tag{2.13}$$

$$\begin{aligned} \mathbf{E}\left(r^e_i\right) = & \ b_1 cov\left(r^e_i, r_{MRKT}\right) + b_2 cov\left(r^e_i, r_{SMB}\right) \\ & + b_3 cov\left(r^e_i, r_{HML}\right) + b_4 cov\left(r^e_i, r_{MOM}\right) \\ & + b_5 cov\left(r^e_i, r_{LIQ}\right) + b_6 cov\left(r^e_i, r_{HCMLC}\right) \end{aligned} \tag{2.14}$$

$$\begin{aligned} \mathbf{E}\left(r^e_i\right) = & \ \lambda_{MRKT}\beta_{i,MRKT} + \lambda_{SMB}\beta_{i,SMB} \\ & + \lambda_{HML}\beta_{i,HML} + \lambda_{MOM}\beta_{i,MOM} \\ & + \lambda_{LIQ}\beta_{i,LIQ} + \lambda_{HCMLC}\beta_{i,HCMLC} \end{aligned} \tag{2.15}$$

r^e_i denotes stock or portfolio i's excess return, $\beta_{i,j} = \mathbf{CV}\left(r^e_i, r_{j,t}\right)/\mathbf{V}\left(r_{j,t}\right)$, and λ_j is the price of risk associated with the j'th factor. Eqn. (2.12) is the no-arbitrage condition stating that risk-adjusted stock returns have a price of zero and eqn. (2.13) specifies the linear form of the SDF. The beta pricing models in eqns. (2.14) and (2.15) are immediately implied. Eqn. (2.15) is estimated with the Fama-MacBeth (1973) two-stage regressions at the firm level without sorting the stocks into portfolios. 60-month rolling regressions are used in the first stage and the intercept term is excluded in the second stage regression. An intercept term is excluded in the second stage to avoid the restriction of a common underpricing or overpricing in the cross-section of returns that would result. Fama-MacBeth regressions are run with the HCMLC portfolio as the only factor, augmenting the CAPM with HCMLC, augmenting the FF3F model with HCMLC, and augmenting the FFCPS model with HCMLC.

Table 2.6 presents risk premium results from the firm-level Fama-MacBeth regressions. The coefficient representing the HCMLC risk premium is stable across factor specifications. When HCMLC augments the CAPM, a risk premium of 5.4 percent is obtained. This premium is in line with the 6.0 percent sample mean return observed on the HCMLC portfolio. When the FF3F model is augmented with the HCMLC factor, a financial contagion risk premium of 4.0 percent is obtained. The estimated risk premium is 3.9 percent when the FFCPS model is augmented and it is 9.6 percent when HCMLC is the only factor. In all factor specifications, financial contagion risk premiums are statistically significant at the one percent level and of roughly the same magnitude as the market risk premium.

Table 2.7 presents results of Fama-MacBeth regressions for a number of test portfolios. The test portfolios include the 49 industry portfolios, the 10 size sorted portfolios, the 10 B/M sorted portfolios, the 10 momentum sorted portfolios, and the combination of the 25 size-B/M sorted portfolios and 10 momentum portfolios. Industry and momentum portfolios are included, in addition to the traditional size and B/M sorted ones, to satisfy "prescription 1" of Lewellen, Nagel, and Shanken (2010) for improving asset pricing tests since they do not correlate as highly with the SMB and HML returns. Results for both equally-weighted test portfolios and value-weighted test portfolios are presented. Financial contagion risk is significantly priced in all of the cross-sections of test portfolios. Also of note is the large financial contagion risk premium that the momentum portfolios price in. The annualized financial contagion risk premium for the ten momentum portfolios is 23.4 percent when the momentum portfolios are formed from equally-weighted stocks. Generally, however, the financial contagion risk premiums implied by the test portfolios are in the range of 5-15 percent. Statistically significant financial contagion risk premiums for the industry portfolios, size portfolios, B/M portfolios, and 25 size-B/M plus 10 momentum portfolios are 4.7 percent, 15.6 percent, 14.9 percent, and 5.8 percent, respectively.

Table 2.8 formally tests if the out of sample Fama-MacBeth pricing errors are jointly equal to zero for each of the factor model specifications. The Chi-square test is used to test if all pricing errors are significantly different from zero

$$\widehat{\boldsymbol{\alpha}} = T^{-1}\sum_{t=1}^{T}\widehat{\boldsymbol{\alpha}}_t,\ cov\left(\widehat{\boldsymbol{\alpha}}\right) = T^{-2}\sum_{t=1}^{T}\left(\widehat{\boldsymbol{\alpha}}_t - \widehat{\boldsymbol{\alpha}}\right)\left(\widehat{\boldsymbol{\alpha}}_t - \widehat{\boldsymbol{\alpha}}\right)',\ \widehat{\boldsymbol{\alpha}}' cov\left(\widehat{\boldsymbol{\alpha}}\right)\widehat{\boldsymbol{\alpha}} \sim \chi^2_{N-k} \qquad (2.16)$$

where $\widehat{\boldsymbol{\alpha}}_t$ is the vector of residuals in eqn. (2.15) estimated from the second-stage Fama-MacBeth regressions at each date, N is the number of portfolios, and k is the number of factors in the model. Pricing error results from the CAPM, FF3F, and FFCPS models are presented in columns two to four. Pricing error results when the HCMLC factor is the only factor are presented in the final column. The null hypothesis that pricing errors are jointly all equal to zero is generally rejected for all factor models and test portfolios. The HCMLC factor alone, however, prices assets at least as well as the other models in all cases and better than the CAPM and FF3F models for the 49 industry portfolios, the 10 B/M portfolios, and the 25 size-B/M plus 10 momentum portfolios. That the HCMLC factor alone prices assets so successfully out of sample shows that financial contagion risk is an important source of the risk premium.

In addition to the out of sample Fama-MacBeth cross-sectional regressions, the price of contagion risk is also estimated in ex-post full sample two-pass cross-sectional regressions. Risk premium parameters in eqn. (2.15) are estimated using regular ordinary least squares (OLS) and two alternative specifications of feasible generalized least squares (FGLS). GLS estimators are included to accommodate the empirical regularity that the residuals from estimating models of the eqn. (2.15) are correlated. The two FGLS specifications differ in the assumed structure of the error variance matrix, $\boldsymbol{\Omega}_j$ for $j \in \{1, 2\}$. In the first specification, denoted GLS_1, errors are allowed to be heteroskedastic. Possible heteroskedasticity in the error variance is modeled as

$$\overline{\boldsymbol{r}}^e = \widehat{\mathbf{B}}\boldsymbol{\Lambda} + \boldsymbol{v} \tag{2.17a}$$

$$\widehat{\boldsymbol{v}}^2 = \left(\overline{\boldsymbol{r}}^e - \widehat{\mathbf{B}}\widehat{\boldsymbol{\Lambda}}_{OLS}\right) \circ \left(\overline{\boldsymbol{r}}^e - \widehat{\mathbf{B}}\widehat{\boldsymbol{\Lambda}}_{OLS}\right) \tag{2.17b}$$

$$ln\left(\widehat{\boldsymbol{v}}^2\right) = c_0 + \widehat{\mathbf{B}}\mathbf{C} + \boldsymbol{u} \tag{2.17c}$$

$$\widehat{\widehat{\boldsymbol{v}}}^2 = exp\left(\widehat{c}_0 + \widehat{\mathbf{B}}\widehat{\mathbf{C}}\right) \tag{2.17d}$$

$$\widehat{\boldsymbol{\Omega}}_1 = diag\left(\widehat{\widehat{\boldsymbol{v}}}^2\right) \tag{2.17e}$$

Hats above variables denote that they have been estimated and $\circ$ denotes the Hadamard element-by-element multiplication operator. Eqn. (2.17a) is the standard cross-sectional OLS equation corresponding to eqn. (2.15). $\overline{\boldsymbol{r}}^e$ denotes mean portfolio excess return. c_0 and $\mathbf{C}$ are a coefficient and a vector of coefficients to be estimated with eqn. (2.17c). $\widehat{\mathbf{B}}$ is the matrix of estimated betas where row i of $\widehat{\mathbf{B}}$ is the transposed vector of beta coefficients estimated for portfolio i from eqn. (2.11). $\boldsymbol{\Lambda}$ is the vector of factor risk premium coefficients to be estimated in eqn. (2.15). Since $\boldsymbol{\Omega}_1$ is a diagonal matrix, GLS_1 is also the weighted least squares (WLS) estimator of risk-premiums. The second specification for the FGLS error variance matrix allows for correlated residuals across portfolios in eqn. (2.11)

$$\widehat{\boldsymbol{\varepsilon}}_i = \boldsymbol{r}_i^e - \mathbf{F}\widehat{\boldsymbol{\beta}}_i \tag{2.18a}$$

$$\widehat{\boldsymbol{\Omega}}_2^{(i,j)} = \frac{\widehat{\boldsymbol{\varepsilon}}_i'\widehat{\boldsymbol{\varepsilon}}_j}{(T-k)} \tag{2.18b}$$

Eqn. (2.18a) is eqn. (2.11) in matrix form and $\widehat{\boldsymbol{\Omega}}_2^{(i,j)}$ denotes the (i, j) element of the

$\widehat{\mathbf{\Omega}}_2$ matrix.

Table 2.9 presents the cross-sectional risk premium results. Standard errors for the OLS regression are White (1980) heteroskedasticity consistent standard errors adjusted by the Shanken (1992) correction to account for portfolio betas being estimated in the first step. FGLS standard errors are also adjusted by the Shanken (1992) correction. Shanken correction factors are presented in the final column of the table. In the cross section, financial contagion risk is priced in all sets of test portfolios. Conservative estimates of the financial contagion risk premium estimated from the 49 industry portfolios, 10 size portfolios, 10 B/M portfolios, 10 momentum portfolios, and 25 size-B/M plus 10 momentum portfolios are 5.6 percent, 12.8 percent, 10.1 percent, 46.0 percent, and 10.2 percent, respectively. These risk premium results are generally close to the observed sample mean HCMLC portfolio return. Momentum portfolios, however, continue to price a large HCMLC risk premium. Adjusted R^2 statistics from estimating eqn. (2.15) with all factors are presented in the second to last column and adjusted R^2 statistics from estimating eqn. (2.15) without the HCMLC factor are presented in the third to last column. Model fit, measured by adjusted R^2, is improved by including the HCMLC factor in the 10 size portfolios, 10 momentum portfolios, and the 25 size-B/M plus 10 momentum portfolios. The largest increase in fit occurs for the 10 size portfolios where GLS_1 adjusted R^2 increases from 0.665 to 0.889. OLS adjusted R^2 increases from 0.794 to 0.898. Note that since OLS, GLS_1, and GLS_2 each have different assumed error variance matrix, adjusted R^2 levels are not directly comparable across estimators. The change in adjusted R^2 for a given estimator is the statistic of interest.

Table 2.10 presents chi-square statistics testing if the ex-post pricing errors from the cross sectional regressions are jointly equal to zero. The test statistic with the Shanken (1992) correction is

$$cov\left(\widehat{\boldsymbol{\alpha}}\right) = \frac{1}{T}\left(\boldsymbol{I}_N - \widehat{\boldsymbol{\beta}}\left(\widehat{\boldsymbol{\beta}}'\widehat{\boldsymbol{\beta}}\right)^{-1}\widehat{\boldsymbol{\beta}}\right)\boldsymbol{\Sigma}\left(\boldsymbol{I}_N - \widehat{\boldsymbol{\beta}}\left(\widehat{\boldsymbol{\beta}}'\widehat{\boldsymbol{\beta}}\right)^{-1}\widehat{\boldsymbol{\beta}}\right)' \times \left(1 + \widehat{\boldsymbol{\lambda}}'\boldsymbol{\Sigma}_f\widehat{\boldsymbol{\lambda}}\right) \tag{2.19a}$$

$$\widehat{\boldsymbol{\alpha}}' cov\left(\widehat{\boldsymbol{\alpha}}\right)\widehat{\boldsymbol{\alpha}} \sim \chi^2_{N-k} \tag{2.19b}$$

where $\widehat{\boldsymbol{\alpha}}$ is the vector of estimated residuals from estimating eqn. (2.15), $\widehat{\boldsymbol{\beta}}$ is the matrix of estimated factor loadings obtained from eqn. (2.11) and used in estimating eqn. (2.15), $\boldsymbol{\Sigma}$ is the variance-covariance matrix of estimated residuals from eqn. (2.11), $\boldsymbol{\Sigma}_f$ is the variance-covariance matrix of factor returns, and $\widehat{\boldsymbol{\lambda}}$ is the vector of prices of risk obtained from estimating eqn. (2.15) with OLS. Ex-post, HCMLC prices the test portfolios approximately as well as MRKT does. Ex-post, however, the FF3F model and the FFCPS models perform substantially better than the HCMLC model. This is to be as expected given the full sample of data and the additional dimensions with which the additional factors can match the data. Out of sample pricing errors, however, where the HCMLC model performs at least as well as the multifactor models is arguably the more important test of pricing ability.

2.6 Robustness

This section tests for beta estimation window robustness and subsample consistency of the price of financial contagion risk. Table 2.11 presents second-stage risk-premium results from Fama-MacBeth regressions using the firm level common stock sample and using first-stage beta estimation windows ranging from 48 months to 120 months. With all estimation windows, the HCMLC portfolio obtains a significant risk premium at the one percent significance level. HCMLC risk premiums range from a low of 3.7 percent when the beta estimation window is 48 months to a high of 4.8 percent when the beta estimation window is 120 months.

Table 2.12 presents risk premium results for value-weighted test portfolios when the beta estimation window is varied in first-stage Fama-MacBeth regressions. Only risk-premium results for the HCMLC portfolio are presented to conserve space. Financial contagion risk premium results are robust across beta estimation windows for the 49 industry, 10 B/M, and 10 momentum portfolios. HCMLC risk-premiums are significantly different from zero for the 10 size portfolios when a 60-month beta estimation window is used and risk-premiums are only significant with 48-month or 84-month beta estimation windows for the 25 size-B/M plus 10 momentum portfolios. Of those significant HCMLC risk premiums estimated, the risk premium generally falls within 5.5 percent and 15.0 percent, in line with results presented earlier.

Subsample consistency of the financial contagion risk premium is tested in Table 2.13 using the firm level common stock sample. Risk premium results from firm level second-stage Fama-MacBeth regressions during non-overlapping five year periods between 1975 and 2010 are presented. The five-year period prior to a five-year window beginning is used to compute the initial betas for the Fama-MacBeth regressions. For example, the cross-sectional test in January 1975 uses betas estimated from January 1970 to December 1974, the cross-sectional regression in February 1975 uses betas estimated from February 1970 to January 1975, and so on until the last cross-sectional regression in the 1975-1979 window would use betas estimated from January 1975 to November 1979. Estimated financial contagion risk premiums are robust to subsample window with risk premiums being significantly priced in the cross-section of stocks during the 1975-'79, 1985-'89, 1990-'94, and 1995-'99 periods. Estimated HCMLC risk premiums in these periods are 3.4 percent, 6.4 percent, 5.5 percent, and 8.3 percent, respectively. Regression slope and Kendall's tau estimates are presented in the final two columns. The null hypothesis of no monotonic relationship between decile HCMLC beta and decile mean return is rejected in the 1980-'84, 1995-'99, and 2000-'05 periods. During these periods, the average additional expected return that investors require to hold an adjacent stock decile with greater HCMLC beta is 83 basis points. Although not statistically significant in every subsample, in each 5-year subsample, investors require additional expected return to hold an adjacent portfolio with higher HCMLC beta except for the 2005-'10 period. In the 2005-'10 period, there is an insignificant negative relationship between HCMLC beta and portfolio return due to the financial crisis.

Figure 2.7 plots the smoothed time series of financial contagion premiums estimated from firm-level Fama-MacBeth regressions. Shaded regions in the top panel are NBER recession dates and shaded regions in the bottom panel are U.S. banking crises dates from Reinhart and Rogoff (2011). The smoothed time series is obtained from running the following smoother twice

$$\widehat{\widehat{\lambda}}_{HCMLC} = \sum_{m=-h}^{h} \left[\frac{h+1-|m|}{(h+1)^2} \right] \widehat{\lambda}_{HCMLC} \tag{2.20}$$

where $h = 23$ (5 percent of the sample size). In the top panel of Figure 2.7, the HCMLC risk premium generally increases slightly during recessionary times. In the bottom panel, the HCMLC risk premium increases substantially during U.S. banking crises. The large peak in financial contagion that occurs outside of U.S. recessionary and banking crisis periods coincides with the Asian financial crisis. Figure 2.7 shows that investors demand a higher risk premium on stocks more susceptible to financial contagion risk during banking crises and to a lesser extent recessionary periods that are not primarily banking related.

2.7 Conclusion

Financial intermediaries serve as agents investing on households' behalf making them uniquely able to affect households' consumption opportunity sets. As the propensity for intermediaries to experience shocks simultaneously either endogenously or exogenously increases, households' payoffs experience greater covariation with their consumption possibilities. Modern portfolio theory proposes that assets that experience greater covariation in returns with aggregate consumption require a higher expected return. Therefore, investors will require a greater expected return on assets that covary more strongly with contagious intermediaries.

This paper contributes to the growing financial intermediary asset pricing literature by estimating intermediaries' contributions to aggregate financial contagion in a new state space framework and showing that financial contagion risk is priced in the cross section of stock returns. The financial contagion risk factor (HCMLC) is defined as the portfolio that buys the decile of financial intermediaries that contribute the most to financial contagion and sells the decile of intermediaries that contribute the least to financial contagion. Intermediaries in the high contagion decile outperform those in the low contagion decile by a risk-adjusted 3.9 percent. A monotonic relationship cannot be rejected between expected returns and financial contagion risk. Investors require an additional 80 basis points in expected return to hold an adjacent decile of financial institutions that experiences greater contagion risk and investors require an additional 40 basis points in expected return to hold an adjacent stock decile with greater financial contagion beta.

Intermediary contagion risk is priced in the out of sample cross-section of firm level common stock returns. Intermediary contagion risk is also priced in the ex-post cross-section of test portfolio returns that are sorted on size, B/M, momentum, and industry. The estimated risk premium of the HCMLC is generally within 5 percent to 15 percent, which is in line with the sample mean of 6 percent that the HCMLC portfolio obtains. Out of sample, the HCMLC factor prices portfolios at least as well as the CAPM, FF3F, and FFCPS models with superior pricing performance relative to the CAPM and FF3F models for the 49 industry portfolios, 10 B/M portfolios, and the 25 size-B/M plus 10 momentum portfolios. Risk premium results are robust to beta estimation window in Fama-MacBeth regressions and time period tested.

Ex-post, including the HCMLC factor in the FFCPS model also substantially improves model fit. Ex-post adjusted R^2 for modeling mean returns for the 10 size portfolios increases from 0.665 with the FFCPS to 0.889 once the HCMLC factor is included. Adjusted R^2 increases are also observed in the 10 momentum portfolios and the 25 size-B/M plus 10 momentum portfolios. The results in this paper indicate that financial contagion risk has important implications for asset prices and is an important source of the risk premium.

3 An ETF Premium Puzzle and a Market Segmentation Explanation

Over the past decade funds invested in exchange traded funds (ETFs) have grown significantly from \$100 billion in 2000 to \$1 trillion in 2010. Exchange traded funds (ETFs) are investment vehicles that are hybrids between traditional open-end mutual funds and closed-end funds. ETFs invest in a basket of securities and issue shares, representing claims to the underlying net asset value (NAV) of the fund, that trade on stock exchanges as common stocks do. Unlike open-end funds, shareholders generally cannot redeem shares at NAV directly and dissimilar to closed-end funds, the amount of shares outstanding can vary over time due to the creation/redemption arbitrage mechanism that is unique to ETFs.

In a frictionless market, ETF share prices will equal NAV. If this were not the case, then a riskless arbitrage opportunity would exist. To the contrary, this paper finds that ETFs persistently trade at a premium. In 89 percent of sample months, mean ETF share prices are greater than NAV. The fraction of ETFs trading at a premium is persistently greater than the one percent critical value that would exist if premiums and discounts were equally likely. Further, mean premium half-lives range from 0.574 days for ETFs that invest in domestic equities to 8.891 days for ETFs that invest in domestic fixed income. The full sample mean premium is a statistically significant 11.6 basis points, with the sample mean premium of ETFs ranging from 2.6 basis points for ETFs that invest in U.S. equities to 68.4 basis points for ETFs investing in foreign fixed income. This is a puzzling result in the presence of capitalized management fees, expenses, and replication transaction costs. ETFs track passive indices in which case fees cannot be linked to managerial skill as in Berk and Stanton (2007). It follows that investors should demand a discount to NAV as is commonly observed in the closed-end fund market.

ETFs provide a means for investors to gain access to a cash flow stream indirectly that may be inaccessible completely or only accessible at a high cost otherwise. If markets are segmented and ETFs provide liquidity benefits to investors, then rational investors should be willing to pay a premium to NAV as long as the cost of the premium is less than the liquidity and diversification benefits received. This is the main hypothesis tested in this paper. Tracking error standard deviation ($TESD$), the standard deviation of the difference between NAV returns and returns on the basket of securities that it aims to replicate, is used in this paper as the measure of market segmentation. In more segmented markets, ETF managers are expected to have less precise tracking ability.

$TESD$ is found to be positively related to premiums after controlling for fund characteristics, transaction costs, and tax overhang liabilities. A 100 basis point increase in $TESD$ increases premiums by 13.5 basis points in the full sample of ETFs. Accessibility to foreign securities and fixed income securities through ETFs are revealed to be the most valuable to investors. Whereas a 100 basis point increase in $TESD$s for foreign and fixed income ETFs increase premiums by 16.6 basis points and 48.9 basis points, respectively, 100 basis point increases in $TESD$s for domestic and equities ETFs increase premiums by 7.0 basis points and 11.8 basis points, respectively. Increased market segmentation also slows the speed of premium correction. A 100 basis point increase in the tracking error standard deviation leads to a premium correction speed that is 2.6 days slower.

Alternative hypotheses about premium dynamics include the contingent tax liability hypothesis and the investor sentiment hypothesis. Malkiel (1977) and Day, et al. (2011) find that closed-end fund discounts widen as the level of contingent tax liabilities increase and that discounts shrink as the level of contingent tax liabilities decreases. This paper finds no evidence of a similar tax-related pattern in the ETF market. The investor sentiment and noise trading hypotheses, stating that irrational noise traders create a form of idiosyncratic risk that deters rational risk-averse arbitrageurs from trading, was introduced by De Long, et al. (1990) with initial empirical support being provided by Lee, et al. (1991) in the closed-end fund market. Bodurtha, et al. (1995), Gemmill and Thomas (2002), and Neal and Wheatley (1998) further provide empirical evidence that closed-end fund discounts are affected by investor sentiment. Recent work showing that investor sentiment is a contrarian predictor of returns includes Baker and Wurgler (2006), Baker, et al. (2012), Ben-Rephael, et al. (2012), Frazzini and Lamond (2008), and Lemmon and Portniaguina (2006). Similarly, this paper finds that investor sentiment affects premium levels in the ETF market. ETF premiums are found to be a contrarian predictor of NAV returns, market returns, and returns on the small-minus-big portfolio at the three-month holding period horizon. After controlling for traditional measures of investor sentiment, $TESD$ continues to have explanatory power for ETF premiums.

Since tracking error standard deviation is used as the measure of market segmentation in this paper, tests are run to validate that its properties are consistent with those desirable for a market segmentation measure. Trading costs that increase market segmentation such as illiquidity and variance also increase $TESD$. Further, ETFs investing in securities that trade in foreign markets have larger tracking error standard deviations than ETFs that invest in domestic securities. The results in this paper confirm that $TESD$ is a robust measure for market segmentation and other studies can also benefit from using $TESD$ as a market segmentation measure where market segmentation or barriers to entry are difficult to measure.

Cherkes, et al. (2009) and Ramadorai (2012) are the papers that are most similar to this one. Cherkes, et al. develop a model in which closed-end fund discounts are rationally governed by the tradeoff between liquidity benefits that the closed-end fund provides and capitalized management fees that reduce fund value. Empirically, they show that investors are willing to pay a liquidity premium in the closed-end fund market which is consistent with their model. Ramadorai find that investors are also willing to pay a premium to NAV for liquidity benefits in the secondary market for hedge funds. Similar papers showing that investors are willing to pay a premium to NAV for liquidity benefits regarding international diversification benefits include Bonser-Neal, et al. (1990) and Nishiotis (2004). They, respectively, find that closed-end fund premiums significantly decrease following a decrease in country investment restrictions and that investors are willing to pay a larger premium to NAV if a country has greater indirect investment barriers. More recently Elton, et al. (2013) show that investors view leverage as another market segmenting variable. They find that investors are willing to pay a higher premium for closed-end bond funds that use greater leverage.

The remainder of the paper is organized as follows. Section 1 presents details on how ETFs are structured and on the creation/redemption arbitrage mechanism. Section 2 discusses the data sample used. ETF premium and tracking error methodologies are presented in section 3. Section 4 contains the empirical results. Section 5 contains concluding remarks.

3.1 ETF Structure

ETFs invest in a basket of securities and issue shares representing claims to the underlying net asset value (NAV) of the fund that trade on stock exchanges as common stocks do. For an ETF to be created, a 'sponsor' (ETF manager) files with the SEC. Once approved, the sponsor forms agreements with a number of 'authorized participants' (APs) that have the exclusive rights to create and redeem ETF shares. These APs are institutional investors and market makers. All other investors are generally only able to purchase and sell ETF shares in the stock market with other investors. To gain an ETF share, an AP must deposit the underlying securities that the ETF aims to replicate with the fund and in return receives a 'creation unit' in kind. This creation unit is a large block of ETF shares, ranging in size from 20,000 to 600,000 shares. To redeem a creation unit, an AP accumulates enough ETF shares to form a creation unit and returns this to the ETF fund manager in exchange for the underlying assets in kind. Unlike open-end mutual funds, ETFs cannot be redeemed directly by market participants other than APs and dissimilar to closed-end funds, the number of shares outstanding can vary over time. In addition to investing in the index that an ETF aims to replicate, ETFs also engage in securities lending. Interest income from securities lending can be used to offset NAV decay that arises from management expenses and trading costs.

Creation/redemption possibilities create an approximately risk-free arbitrage opportunity for APs. If an ETF share price is greater than its NAV, then an AP can buy the monetary value of a creation unit of underlying portfolio securities, form a creation unit, and sell that creation unit in the stock market. The arbitrage profit would be the amount that the ETF share price is in excess of its NAV. If an ETF share price is lower than its NAV, then an AP can buy enough ETF shares in the stock market to form a creation unit, swap this for an equal monetary value of the underlying securities, and sell these securities on the open market. In this case, the arbitrage profit would be the amount that NAV is in excess of the ETF share price. In some instances, an 'optimized' portfolio of securities may also be used to create/redeem creation units. This optimized portfolio allows cash to substitute in place of more illiquid underlying securities.

3.2 Data and ETF Characteristics

ETF data is hand collected for the March 1996 to December 2011 period from the iShares website and from the CRSP daily stock file database. iShares' earliest ETFs were conceived on March 12, 1996. ETF net asset values (NAV), underlying index levels, management fees, inception dates, creation unit sizes, and creation/redemption costs are hand collected from the iShares website[1,2]. All ETFs included in the sample are standard unlevered ones.

Daily ETF closing market prices, closing bid prices, closing ask prices, daily volumes, number of shares outstanding, and dividend distribution amounts are obtained from CRSP. Short rate data, market portfolio (MRKT) return data, and small-minus-big portfolio (SMB) return data are collected at the daily frequency from Kenneth French's website. Since NAVs recorded by iShares are already adjusted for splits, CRSP prices are adjusted for splits by dividing price by the CRSP cumulative factor to adjust prices (CFACPR). Dividends are added back into NAV on ex-div dates for tracking error calculations when target index returns are total returns. Observations recorded on weekends or holidays in the iShares data or CRSP data are removed from the sample. If the number of missing price, index, or NAV data as a proportion of an ETF's total observations exceeds five percent, then the ETF is dropped from the sample.

[1]NAV data is downloaded from `http://tools.ishares.com/tec2/download_data.do`. Management fees and inception dates are downloaded from `http://us.ishares.com/product_info/fund/index.htm`.

[2]iShares ETFs have made up roughly 50 percent of all ETF assets since 2005 (Petajisto (2011))

In rare instances, there are NAV data errors in the iShares data that result in ETF price and NAV differing by more than 20 percent. After manual inspection to verify that a premium in excess of twenty percent is in fact an error, the erroneous observation and the following observation are removed. All premiums in excess of twenty percent are, however, not erroneous. For example, the Malaysia ETF consistently experienced differences between price and NAV in excess of 20 percent in the first two weeks of May 1999. In total there are 370,974 daily ETF observations and 224 ETFs in the final sample.

Figure 3.1 presents the time series of the number of ETFs contemporaneously included in the sample. The number of ETFs increases monotonically from 17 in 1996 to 224 in 2011. Total assets under management (AUM) of ETFs contemporaneously present in the sample is plotted in Figure 3.2. AUM has increased dramatically since iShares' first ETF inception in 1996, increasing from \$0.05 billion in March 1996 to \$399 billion in December 2011.

ETF fund characteristics are presented in Table 3.1. Fund classifications are obtained from Yahoo Finance. For the full sample, mean ETF market-cap is \$1.445 billion and mean daily trading volume is in excess of one million shares per day. Mean ETF expense ratio is 40 basis points, mean creation unit size is 91,825 shares, and mean per share creation/redemption percentage cost is 6.4 basis points. ETF characteristics vary widely across ETF types. The largest mean market-cap is in excess of \$2 billion for ETFs investing in U.S. fixed income. The smallest ETFs are ETFs that invest in foreign fixed income with a mean market-cap below \$0.5 billion. Expense ratios are largest for ETFs investing in foreign equities at 52.3 basis points. Mean creation unit size is largest for ETFs investing in foreign equities at 154,359 shares. Creation/redemption per share costs are less than 6 basis points for all ETF types except for foreign equities for which it is 13.6 basis points.

3.3 ETF Premiums and Tracking Errors

3.3.1 Premium Synchroneity Adjustment

ETF premiums are defined as

$$PREM_{i,t} = ln\left(P_{i,t}/NAV_{i,t}\right) \times 100 \tag{3.1}$$

where $P_{i,t}$ is an ETF's nominal market price at the close of day t and $NAV_{i,t}$ is its recorded nominal NAV for day t. Recorded NAVs for ETFs investing in foreign securities are not synchronous with their respective ETF market prices on the U.S. stock market. Underlying index values are recorded using closing prices from the index's domestic market and foreign exchange rates used are those recorded at 4 p.m. London time (11 a.m. Eastern time). Since additional information is impounded into market prices over the remainder of U.S. trade, absolute premiums appear larger than they actually would be if there was synchronous trade. To account for the continuing information flow, the efficient NAV pricing model of Goetzmann, et al. (2001) is used with the Engle and Sarkar (2006) specification to estimate synchronous NAVs for ETFs investing in foreign equities and foreign fixed income. The premium adjustment model is

$$ln\left(P_{i,t}\right) - ln\left(NAV_{i,t}\right) = \alpha_i \triangle ln\left(NAV_{i,t}\right) + \phi_i r_{MRKT,t} + u_{i,t} \tag{3.2a}$$

$$\widehat{NAV}^*_{i,t} = exp\left[ln\left(P_{i,t}\right) - \widehat{u}_{i,t}\right] \tag{3.2b}$$

where $r_{MRKT,t}$ is the daily return on the U.S. market portfolio and $\triangle$ is the difference operator. α_i and ϕ_i are coefficients to be estimated and the estimated true synchronous NAV, $\widehat{NAV}^*_{i,t}$, is given by eqn. (3.2b). The estimated true premium, $ln\left(P_{i,t}\right) - ln\left(NAV^*_{i,t}\right)$, is the regression residual, $\widehat{u}_{i,t} \times 100$. Motivated by the findings of Bodurtha, et al. (1995) that prices of closed-end funds invested in foreign securities significantly commove with U.S. market returns, the market portfolio return is used as an explanatory variable for premiums. If there is no measurement error in recorded premiums, then $\alpha_i = \phi_i = 0$ and $ln\left(P_{i,t}\right) - ln\left(NAV_{i,t}\right) = \widehat{u}_{i,t}$. In the presence of information continuing to be impounded into domestically traded ETF prices, NAV returns and/or domestic market returns will have explanatory power for premiums and the variance of adjusted premiums will be significantly smaller than the variance of recorded premiums.

Results from estimating eqns. (3.2a)-(3.2b) are presented in Table 3.2. Panel A shows that both NAV returns and U.S. market returns have significant explanatory power for premiums. The mean values for α and ϕ are -0.104 and 0.004, respectively. These values indicate that recorded premiums are smaller when NAV returns are larger and that premiums are larger when U.S. market returns are larger. The twenty-fifth (seventy-fifth) percentiles of estimated α and ϕ across foreign ETFs are -0.145 (-0.050), and 0.003 (0.006), respectively. Panel B presents the ratios of recorded premium sample variance to estimated synchronous premium sample variance for each of the adjusted ETFs. Premium variance equality is tested for by using the F-test. Generally, variance ratios are significantly greater than one at the one percent significance level. Variance ratios range from a low of 0.961 (insignificantly different from one) to a high of 3.414. Table 3.2 provides evidence that there is substantial measurement error in recorded premiums. To see this, the premium variance ratio can be written as

$$VR_i = \frac{\mathbf{V}\left[PREM_i + \eta_i\right]}{\mathbf{V}\left[PREM_i\right]} = 1 + \frac{\mathbf{V}\left[\eta\right]}{\mathbf{V}\left[PREM_i\right]} \tag{3.3}$$

where $PREM_i$ is the true synchronous premium, η_i is a mean zero measurement error present in recorded nonsynchronous premiums that is independent of $PREM_i$, and $\mathbf{V}\left[\cdot\right]$ is the variance operator. As is evidenced in Table 3.2 Panel B, it is not uncommon for the variance of the measurement error to be in excess of the variance of the true premium. Estimated synchronous premiums for ETFs investing in foreign securities, obtained from eqns. (3.2a,b), are used in the remainder of the paper to avoid the results simply being an artifact of nonsynchronous prices.

3.3.2 ETF Premiums

ETF premium statistics are presented in Panel A of Table 3.3. The sample mean premium across all ETFs is a statistically significant 11.6 basis points. The mean premium is lowest for U.S. equities at 2.6 basis points and highest for foreign fixed income at 68.4 basis points. Mean premiums for U.S. fixed income and foreign equities are 37.1 basis points and 15.9 basis points. All ETF types display large premium sample standard deviations. The sample standard deviation of premiums for all ETFs is 81.8 basis points. The normal range that premiums take is presented in the twenty-fifth and seventy-fifth percentiles. Generally, ETFs investing in U.S. equities have premiums between -8.5 basis points and 11.1 basis points. The twenty-fifth (seventy-fifth) percentiles for premiums of ETFs investing in U.S. fixed income is 2.9 (50.8) basis points. The values are -28.5 (57.8), 19.9 (108.3), and -8.8 (34.5) basis points for ETFs that invest in foreign equities, foreign fixed income, and miscellaneous, respectively.

Figure 3.3 presents a time series plot of within-month mean ETF premiums. Premiums are the greatest prior to the decimalization of the stock market in 2001. Prior to 2001, the mean premium across the iShares space was 44.1 basis points (not reported). Following 2001, mean premiums decreased and remained at more stable levels. Premium magnitudes can also be seen to be larger in times of market stress; consistent with the liquidity benefits that ETFs offer being greater at these times. Figure 3.4 plots the fraction of ETFs with a positive within-month mean premium. One percent significance level critical values for the null hypothesis that ETFs are equally likely to trade at a premium as at a discount are plotted as a dashed line. The fraction of ETFs trading at a premium is persistently greater than the one percent significance level rejecting the null hypothesis that premiums are as likely to occur as discounts.

That ETFs persistently trade at a premium to NAV, is a puzzling result. Similarly to closed-end funds, ETF managers extract management fees and trading costs from NAV. ETF shareholders also receive distributions in the form of dividends which represent a tax liability. In the presence of these capitalized costs, investors should only be willing to pay a discount to NAV for ETF shares similarly to as is commonly found in the closed-end fund market. I propose that liquidity benefits dominate capitalized holding costs in the ETF market and that this is the reason that ETFs persistently trade at a premium to NAV.

3.3.3 NAV Tracking Errors

If an underlying portfolio is perfectly accessible, then the ETF manager will be able to perfectly track the underlying index that it aims to replicate. In the presence of imperfect replicating ability, NAV returns will vary from returns on the portfolio that the ETF aims to replicate. This is called "tracking error" and is defined in this paper as in Tang and Xu (2013) as

$$TE_{i,t} = \left(r_{i,t}^{NAV} - r_{i,t}^{INDEX}\right) \times 100 \tag{3.4}$$

where $r_{i,t}^{NAV}$ is the daily arithmetic NAV return and $r_{i,t}^{INDEX}$ is the daily arithmetic return on the underlying portfolio that the ETF aims to replicate. Table 3.3 Panel B presents tracking error statistics. The sample mean tracking error for the full ETF sample is zero. Only ETFs investing in U.S. fixed income have a mean tracking error that is significantly different from zero with a mean of -0.1 basis points. Market segmentation is measured by the standard deviation of tracking errors in this paper. ETFs investing in securities with greater trading frictions will have greater tracking error standard deviations. Following from the equity premium puzzle, however, the tracking error standard deviation for equities ETFs will naturally be larger than the tracking error standard deviation for fixed income ETFS. This is a minor challenge that can be controlled for in the cross-section with dummy variables for ETF type.

ETFs on foreign equities are the most difficult to replicate with a sample tracking error standard deviation of 0.333 percent. ETFs on U.S. fixed income have the smallest standard deviation of tracking errors at 0.070 percent. The tracking error sample standard deviation of ETFs investing in U.S. equities is 0.177 percent. Twenty-fifth and seventy-fifth percentiles of tracking errors indicate that the distribution of tracking errors is fairly symmetric with the majority of tracking errors falling within the range of -2 basis points and 2 basis points. In rare instances, tracking error magnitudes were as large as 33 percent. This particularly large tracking error occurred for the Malaysia ETF on April 1, 1999.

Figure 3.5 presents a time series plot of within-month mean tracking errors. Generally, mean tracking errors are approximately zero. The period from 1997 and into 1999 is the exception. During the 1997-1999 period the majority of ETFs in the sample are ones invested in Asian countries. As a result of the Asian crisis and fallout, tracking errors were substantially larger than during the rest of the sample period.

3.4 ETF Premiums and Market Segmentation

3.4.1 ETF Premium Determinants

Market segmentation limits the accessibility of certain assets. Gaining exposure indirectly to these securities may be required for mean-variance maximizing investors, however. Rational investors will be willing to pay a premium to NAV for ETFs holding securities in segmented markets as long as the cost of the premium paid is smaller than the diversification and liquidity benefits received. Extant empirical support for this intuition is provided by Bonser-Neal, et al. (1990) and Nishiotis (2004), both of which find that closed-end funds that invest in nations with greater investment barriers tend to trade at greater premiums. Differential trading costs are a second form of market segmentation that reduces realized returns in one market relative to the other. Considering two securities identical in every way except for trading costs, mean-variance maximizing investors will be willing to pay a premium to NAV if the paid premium and illiquidity costs of holding an ETF are less than the trading cost of holding the underlying portfolio that an ETF aims to replicate as in the model of Acharya and Pedersen (2005).

The following panel regression model is used to test how market segmentation affects

ETF premium levels

$$\overline{PREM}_{i,t} = \beta_0 + \beta_1 TESD_{i,t-1} + \beta_2 \overline{BAS}_{i,t-1} + \beta_3 \overline{PI}_{i,t-1} + \beta_4 \overline{FEES}_{i,t-1} \\ + \beta_5 \overline{DIV}_{i,t-1} + \beta_6 \overline{RF}_{i,t-1} + \beta_7 \overline{VAR}_{i,t-1} + \beta_8 \overline{VOL}_{i,t-1} \\ + \beta_9 \overline{SIZE}_{i,t-1} + \beta_{10} \overline{AGE}_{i,t-1} + \beta_{11} \overline{PREM}_{i,t-1} + \varepsilon_{i,t} \tag{3.5}$$

where $PREM$ is ETF premium, $TESD$ is the within-month standard deviation of daily tracking errors, BAS is the percentage bid-ask spread, PI is the Amihud (2002) price impact illiquidity measure, $FEES$ is ETF expense ratio (in percentage points), DIV is ETF daily dividend yield (in percentage points), RF is the one-day accrual rate for the one-month treasury bill rate (in percentage points), VAR is squared ETF market price daily return, $SIZE$ is ETF market-cap (in billions of dollars), and AGE is ETF age (in years). Bars above variables denote within-month means. Lagged values of all exogenous variables are used in order to align with an investor's information set when making the decision of how to allocate their funds. Lagged premium level, $\overline{PREM}_{i,t-1}$, is also included in eqn. (3.5) to control for autocorrelation in premium levels. Since premium levels estimated from eqns. (3.2a,b) may still contain measurement error, eqn. (3.5) is subject to an errors in variables problem. This will increase the standard errors on the explanatory variables, but coefficient estimates will continue to be unbiased. As a result, statistical significance tests are conservative levels of statistical significance.

$TESD$ is expected to increase premiums since liquidity benefits of holding an ETF are greater if there are greater barriers to investment in the underlying securities. BAS and PI are expected to be negatively related to premiums since these trading costs reduce the relative expected return of holding an ETF to holding the underlying securities. This illiquidity discount is modeled in Acharya and Pedersen (2005) where they show that investors are less willing to hold more illiquid securities. Cherkes, et al. (2009), Ramadorai (2012), and Nashikkar, et al. (2011) provide extant empirical evidence in the closed-end fund market, in the Hedgebay secondary market for hedge funds, and in the credit market, respectively, that the more illiquidity of two securities linked by arbitrage trades at a discount to the other.

DIV in the prior month is expected to be positively related to premiums in the current month. New investors will have a smaller contingent tax liability than investors in the previous month and will not demand as large of a discount to NAV. Malkiel (1977) and Day, et al. (2011) find evidence of this tax liability effect in the closed-end fund market. RF and ETF premiums are expected to be negatively related. The short rate affects funding liquidity in that it makes arbitrage trading more costly. More restricted access to capital for arbitrageurs in ETFs may lead to decreased ETF liquidity as in the models of Shleifer and Vishny (1997) and Brunnermeier and Pedersen (2009). As funding illiquidity rises for arbitrageurs ETF illiquidity will also increase providing a disincentive for investors to hold ETFs relative to holding the underlying securities directly.

VAR is expected to be negatively related to premiums following from mean-variance optimizing investors being less willing to hold securities with greater variance. AGE is expected to be negatively related to premium level following from the results of Christoffersen, Errunza, Jacobs, and Langlois (2012) showing that international market integration has increased over time. Increased market integration diminishes the marginal benefit of holding ETFs rather than the underlying securities directly. The relationship between VOL and premiums is ambiguous ex-ante. There is a large body of literature showing that volume and return variance are positively related (See Karpoff (1987) for a survey of the early literature). If this relationship holds in the ETF market as well, then VOL will increase VAR and premium level will be negatively related to VOL following from mean-variance optimization. Greater trading volume, however, also means that there is greater liquidity in the market. If this increased liquidity effect dominates the increased variance effect, then a negative relationship between VOL and premium level should be observed. $SIZE$ also has an ex-ante ambiguous expectations. If $SIZE$ increases as the result of greater money flows into the fund then ETF size and premium will be positively related. In contrast to this, if there are diseconomies of scale in fund size then ETFs may be forced to overweight more liquid holdings, as Pollet and Wilson (2008) show occurs in traditional open-end mutual funds. This over weighting of liquid holdings will reduce the diversification benefits of the ETF providing a disincentive to hold ETF shares. In this case, a negative relationship would be found between $SIZE$ and premium.

Table 3.4 presents the main results of the paper obtained from estimating eqn. (3.5). Column one does not include fixed-effects and only includes a constant term, $TESD$, BAS, PI, and $LPREM$, $\overline{PREM}_{i,t-1}$, as explanatory variables. $TESD$ enters significantly with the correct positive sign. A one percentage point increase in $TESD$, leads to an increase in premiums of 8.9 basis points in the following month. This is not only a statistically significant result, but also an economically significant one. BAS and PI enter insignificantly, indicating that ETFs do not offer significant trading cost benefits relative to the underlying securities.

Column two includes $TESD$, a dummy variable for fixed income ETFs, FI, and a dummy variable for foreign ETFs, FOR. These two asset classes are known to be difficult to invest in and both obtain significantly positive coefficients indicating that investors are willing to pay a premium for indirect access to these securities. The magnitude of the coefficient on the fixed income dummy variable, 12.3 basis points, is larger than the coefficient on the foreign dummy variable, 3.0 basis points, indicating that investors value the liquidity benefits that bond ETFs offer more than the liquidity benefits offered by foreign ETFs. Column three presents results from estimating the full model. $TESD$ continues to enter significantly positively with a coefficient of 9.5 basis points and $SIZE$ obtains a significant positive coefficient as well. RF and AGE obtain significant negative coefficients.

Time fixed effects are included in column four to control for the decimalization of tick values in 2001, as well as for time-varying market conditions. Now, a one percentage point increase in $TESD$ leads to an increase in premiums of 13.5 basis points in the following month. The short rate enters significantly with the appropriate negative sign. The correlation coefficient between the risk-free rate and bid-ask spreads during the sample period is 0.14 (not reported). An increase in funding liquidity increases ETF illiquidity reducing the liquidity benefits that ETFs offer. Consistent with mean-variance optimizing behavior, an increase in VAR leads to a decrease in premiums the following month. AGE enters significantly with a negative sign. The significant 0.652 coefficient on $LPREM$ indicates positive autocorrelation in premium levels. ETF fixed-effects, as well as time fixed-effects, are included in the fifth column. Including ETF fixed-effects controls for heterogeneous fund characteristics. $TESD$, RF, VOL, and $SIZE$ enter significantly with coefficients that are relatively unchanged from column three.

3.4.2 Premium Persistence and Market Segmentation

In addition to affecting the level of ETF premiums, market segmentation is also expected to affect the speed of error correction of premiums by increasing idiosyncratic risk. Previous papers by Baker and Savaşoglu (2002), Doukas, et al. (2010), Gagnon and Karolyi (2010), Kapadia and Pu (2010), and McLean (2010) have shown that idiosyncratic risk is an important limit to arbitrage. Premium error correction speed is estimated within the Engle and Granger (1987) framework. As a first step, the cointegrating relationship between ETF share price and NAV is estimated with the following regression

$$P_{i,t} = c_{i,0} + c_{i,1} NAV_{i,t} + \varepsilon_{i,t} \tag{3.6}$$

The error correction model corresponding to eqn. (3.6) is given by

$$\triangle P_{i,t} = a_{i,1} + a_{i,2}\widehat{\varepsilon}_{i,t-1} + \sum_{j=1}^{k} a_{i,11}(j) \triangle P_{i,t-j} + \sum_{j=1}^{k} a_{i,12}(j) \triangle NAV_{i,t-j} + e_{i,t} \tag{3.7}$$

$a_{i,2}$ measures the speed at which ETF i's premiums correct to zero and will be negative if premiums mean revert. A lag length of five is used in eqn. (3.7) for k to control for possible day of the week patterns in premiums.

Error correction coefficients obtained from estimating eqn. (3.7) are presented in Table 3.5. The mean error correction speed for the full sample of ETFs is -0.437 and is statistically significant. This coefficient implies that premiums have a half-life of 1.207 $(= ln\,(0.5)\,/ln\,(1 - 0.437))$ days. The full ETF sample twenty-fifth and seventy-fifth percentiles of estimated error correction indicate that premiums generally have half-lives between 0.523 days and 8.101 days. ETFs investing in U.S. equities have the quickest premium correction speeds and U.S. fixed income ETFs have the slowest premium correction speeds. Mean premium half-lives for U.S. equities and U.S. fixed income are 0.574 days and 8.891 days. Foreign equities and foreign fixed income ETFs have mean premium half-lives of 3.471 days and 4.116 days. The distributions of premium correction speeds for all ETF types are left skewed as evidenced by median statistics that are greater than mean statistics.

The following regressions are used to test how market segmentation affects the speed at which premiums correct

$$
\begin{aligned}
\widehat{a}_{i,2} = \beta_0 &+ \beta_1 TESD_i + \beta_2 \overline{BAS}_i + \beta_3 \overline{PI}_i + \beta_4 \overline{DIV}_i + \beta_5 \overline{RF}_i \\
&+ \beta_6 \overline{VAR}_i + \beta_7 \overline{VOL}_i + \beta_8 \overline{SIZE}_i + \beta_9 \overline{AGE}_i + \beta_{10} \overline{FEES}_i \\
&+ \beta_{11} CUNIT_i + \beta_{12} CUCOST_i + v_i
\end{aligned}
\tag{3.8}
$$

$\widehat{a}_{i,2}$ is the premium correction coefficient, estimated from eqn. (3.7), $CUNIT$ is the creation unit size and $CUCOST$ is the per creation unit share percentage cost of creating/redeeming a creation unit. Eqn. (3.8) is a cross-sectional regression where $TESD$ is the sample standard deviation of tracking errors for ETF i and bars above variables now denote ETF i sample means. Since eqn. (3.8) has estimated error correction coefficients as the dependent variable, there is an errors in variables problem. Measurement error increases the standard errors of the estimated coefficients on explanatory variables, but coefficient estimates remain unbiased.

$TESD$ is expected to be negatively related to the speed of error correction (positively related to $\widehat{a}_{i,2}$ since it increases arbitrage risk. An increase in $TESD$ also results in persistent liquidity benefits that increases the duration for which investors are willing to hold ETFs at a premium. BAS, PI, $CUNIT$, and $CUCOST$ are expected to be positively related to premium persistence since they widen the region of unprofitable arbitrage.

DIV, RF, VAR, and VOL have ambiguous ex-ante expectations for coefficient sign. DIV will increase premium persistence to the extent that differential treatment of dividends between the ETF and target index creates uncertainty about the true NAV. Conversely, DIV may be negatively related to premium persistence if there is sufficient volatility in the contingent tax liability that dividends represent for investors that hold ETFs. RF is expected to increase premium persistence if funding illiquidity reinforces asset illiquidity which would increase arbitrage risk. On the other hand, higher risk-free rates will result in less demand to borrow securities from ETFs. Less securities lending by ETFs can reduce NAV uncertainty since NAV will more closely track its target index in the absence of the lending interest income.

VAR will be positively related to premium persistence to the extent that increased variance increases the difficulty of performing an arbitrage strategy before prices change dramatically. VAR, however, may also be negatively related to premium persistence if increased price variance results in greater price variability centered on no arbitrage prices. In this case increased price variance will lead to an increased number of oscillations from positive to negative premiums. VOL will increase premium persistence if it is primarily sentiment driven creating greater idiosyncratic arbitrage risk. On the other hand, VOL will decrease premium persistence if it is primarily arbitrage driven. $SIZE$ is expected to be positively related to premium persistence since trading larger volumes of money to arbitrage pricing errors increases transaction costs. AGE is expected to be negatively related to premium persistence if arbitrageurs become more skilled over time.

Columns one and two of Table 3.6 present cross-sectional regression results from estimating eqn. (3.8). In column one, $TESD$ significantly increases the amount of time that premiums persist for. A one percentage point increase in $TESD$ is associated with a premium half-life that is 1.402 $(= ln\,(0.5)\,/ln\,(1 - 0.390))$ days longer. Column two includes all variables in the regression. $TESD$ continues to enter significantly with a relatively unchanged coefficient. VOL enters with a negative coefficient providing evidence that volume in ETFs tends to be stabilizing rather than destabilizing. Creation unit size, $CUNIT$, is positively related to premium persistence showing that it is more costly to perform arbitrage strategies with larger creation unit sizes.

Columns three to six present regression estimates obtained from using subsamples of only domestic ETFs, foreign ETFs, equities ETFs, and fixed income ETFs, respectively. $TESD$ has no significant effect on premium correction speed for domestic ETFs and significantly slows premium correction speed for foreign ETFs, equities ETFs, and fixed income ETFs. A one percentage point increase in $TESD$ increases the half-life of premiums of each respective ETF type by 2.443 days, 1.167 days, and 0.301 days. $CUNIT$ is also negatively related to premium correction speed for equities ETFs and fixed income ETFs, but has no significant effect on premium correction speed in the broader subsamples of domestic ETFs and foreign ETFs.

3.4.3 Subsample Robustness

Table 3.7 partitions the ETF sample into a subsample of ETFs that invest domestically and a subsample of ETFs that invest in foreign securities. This is done to test if a subsample of the ETFs is driving the positive relationship between $TESD$ and premium. In the domestic sample, $TESD$ is only significant when only time fixed effects are included obtaining a coefficient of 0.070. PI and VAR enter significantly with a negative sign indicating that investors of domestic ETFs are not willing to pay as high of a premium for less liquid ETFs or for ETFs that have a higher variance. Coefficient estimates for RF and AGE are unstable. RF and AGE obtain negative coefficients when ETF fixed effect are excluded, but obtain positive coefficients when ETF fixed effects are included.

In the foreign sample $TESD$ enters significantly when time fixed effects are included and when ETF fixed effects are additionally included obtaining coefficients of 0.166 and 0.193, respectively. Furthermore the magnitude of the $TESD$ coefficient is larger in the foreign sample than in the domestic sample. This result shows that investors are willing to pay a larger premium for foreign ETFs since they derive greater liquidity and diversification benefits from them. RF only enters significantly and with a negative sign when time fixed effects are included and AGE continues to have an unstable coefficient. ETF premiums in both the domestic sample and the foreign sample experience autocorrelation in premiums as evidenced by the large positive coefficients on lagged premium level.

ETFs are also partitioned into a sample of ETFs that invest in fixed income securities and a sample of ETFs that invest in equities securities. Regression results for these two subsamples are presented in Table 3.8. Evidence that ETFs with higher levels of market segmentation trade at higher premiums is found in both the fixed income sample and the equities sample. The coefficient on $TESD$ is much larger in the fixed income sample implying that liquidity benefits are more valuable to investors wishing to access fixed income securities. When only time fixed-effects are included, the coefficient on $TESD$ is 0.489 in the fixed income sample and the coefficient on $TESD$ is 0.118 in the equities sample. In the fixed income sample the coefficient on $FEES$ is significant, but the wrong sign. $FEES$ enter insignificantly in the equities sample. Both fixed income and equities ETFs have autocorrelated premiums indicated by the large and significant coefficients on lagged premium. Tables 3.7 and 3.8 together show that market segmentation's explanatory power for ETF premiums is not being driven by a single ETF type.

3.4.4 Investor Sentiment Robustness

The main competing hypothesis to the market segmentation hypothesis in explaining premiums is the noise trader hypothesis. Early evidence that investor sentiment plays a significant role in premium fluctuations is provided by Bodurtha, et al. (1995), Gemmill and Thomas (2002), and Lee, et al. (1991) in the closed-end fund market. This subsection tests if $TESD$ continues to have explanatory power for ETF premiums in the presence of investor sentiment effects.

If ETF premiums are affected by sentiment, then as sentiment becomes more optimistic premiums will increase and as sentiment becomes more pessimistic premiums will decrease. U.S. market (MRKT) returns are used as the first measure of investor sentiment, similarly to as in Bodurtha, et al. (1995) and Gemmill and Thomas (2002). Returns on the small-minus-big (SMB) portfolio are used as the second measure of investor sentiment, similarly to as in Lee, et al. (1991), Swaminathan (1996), and Neal and Wheatley (1998). ETF Fund flows ($FLOW$) is used as the third measure of investor sentiment similarly to the flow measures used in Baker, et al. (2012), Ben-Rephael, et al. (2012), Frazzini and Lamont (2008), and Froot and Ramadorai (2008). In this paper, $FLOW$ is defined as

$$FLOW_{i,t} = \frac{\left(AUM_{i,t} - AUM_{i,t-1}\left[1 + RET_{i,t}^{(NAV)}\right]\right)}{AUM_{i,t-1}} \tag{3.9}$$

where $RET_{i,t}^{(NAV)}$ is the daily NAV net return. The investor sentiment variables are included in the following regression

$$\overline{PREM}_{i,t} = \beta_0 + \beta_1 TESD_{i,t-1} + \beta_2 \overline{SENT}_{t-1}^{(k)} + \beta_3 \overline{FEES}_{i,t-1} + \boldsymbol{\phi}'\overline{\mathbf{x}}_{i,t-1} + \varepsilon_{i,t} \tag{3.10}$$

where $k \in \{MRKT, SMB, FLOW\}$. $\overline{\mathbf{x}}$ is a vector of control variables and $\boldsymbol{\phi}$ is the vector of their respective coefficients. Control variables in eqn. (3.10) are the same as those used in eqn. (3.5).

Table 3.9 presents results from estimating eqn. (3.10). The first two columns use within-month mean daily market returns as the sentiment variable, the middle two columns use within-month mean daily returns on the small-minus-big portfolio as the sentiment variable, and the final two columns use within-month mean ETF fund flow as the sentiment variable. $TESD$ continues to obtain a significant positive coefficient in all model specifications. In all model specifications, a 100 basis point increase in $TESD$ is associated with approximately a 13.5 basis point increase in premium level the following month. Lagged market returns and lagged fund flows do not enter significantly in either of the model specifications. The coefficient on lagged SMB returns is significant when only time fixed effects are included and when ETF fixed effects are additionally included.

Recent work showing that investor sentiment is a contrarian indicator for future returns in equities includes Baker and Wurgler (2006), Baker, et al. (2012), Ben-Rephael, et al. (2012), Frazzini and Lamont (2008), Froot and Ramadorai (2008), and Lemmon and Portniaguina (2006). Table 3.10 presents regression results testing if premium level has forecasting ability for future NAV, MRKT, and SMB returns in the ETF market. The regression model used is the model used in Agarwal, et al. (2009) and Ramadorai (2012)

$$\begin{aligned} RET^{(k)}_{i,t+h} = \beta_0 + \beta_1\overline{PREM}_{i,t} + \beta_2\overline{SIZE}_{i,t} + \beta_3\overline{FLOW}_{i,t} + \beta_4\overline{VAR}_{i,t} \\ + \beta_5\overline{AGE}_{i,t} + \beta_6\overline{FEES}_{i,t} + \beta_7 RET^{(k)}_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3.11}$$

where $k \in \{NAV, MRKT, SMB\}$ and $h \in \{1, 3, 6, 12\}$. $RET^{(k)}_{i,t+h}$ is the h-month holding period return. Only coefficient estimates for $PREM$ are presented to conserve space. At the three-month holding period horizon, higher premiums today are associated with lower holding period returns for NAV, MRKT, and SMB. When a holding period of six months is considered, higher premiums today are associated with lower holding period MRKT returns. ETF premiums and holding period returns do not have a significant relationship for NAV, MRKT, and SMB returns when holding periods of one month and twelve months are considered. The negative relationship between three-month holding period returns and current premium level is consistent with the investor sentiment hypothesis. Tables 3.9 and 3.10 show that while there is evidence of investor sentiment effects in the ETF market, after controlling for those effects market segmentation continues to have explanatory power for ETF premiums.

3.4.5 Tracking Error Standard Deviation and Market Segmentation

Since results from the previous sections depend on $TESD$ being a good measure of market segmentation, this section runs tests to validate that $TESD$ has the desirable properties of a segmentation measure. Financial market segmentation can occur for a number of reasons resulting in a set of assets being less accessible than another set of assets, including differing trading costs and barriers to entry. ETFs that aim to replicate less accessible securities are expected to have worse tracking ability. The following regression is used to test how market state contemporaneously affects tracking error standard deviation

$$TESD_{i,t} = \beta_0 + \beta_1 ZEROS_{i,t} + \beta_2 \overline{FEES}_{i,t} + \beta_3 \overline{INDVAR}_{i,t} + \beta_4 \overline{DIV}_{i,t} + \beta_5 \overline{RF}_{i,t} + \beta_6 \overline{SIZE}_{i,t} + \beta_7 \overline{AGE}_{i,t} + \beta_8 TESD_{i,t-1} + \varepsilon_{i,t} \tag{3.12}$$

$ZEROS$ is the illiquidity variable of Lesmond, et al. (1999) and is defined in this paper as the number of within-month trading days that the underlying index had a daily return of zero. $INDVAR$ is the daily squared return of the underlying index. The remaining variables in eqn. (3.12) are defined as before.

$ZEROS$, RF, $INDVAR$, and $SIZE$ are expected to be positively related to $TESD$. $ZEROS$, $INDVAR$, and $SIZE$ result in higher trading costs leading to the replication process becoming noisier. RF will increase the variability of tracking errors either through greater funding illiquidity reinforcing asset illiquidity or by time varying securities lending activities by the ETF fund manager adding additional noise to the replication error. DIV is expected to be positively related to tracking error standard deviation due to the differential treatment of dividends; a similar relationship as to what is found in Callaghan and Barry (2003) in the American depository receipt (ADR) market. AGE is expected to be negatively related to $TESD$ since fund managers are expected to optimize the tracking process over time. Lagged $TESD$ is included to control for ARCH effects in the standard deviation of tracking errors.

Column one of Table 3.11 tests the relative tracking error standard deviation of foreign (FOR) and fixed income (FI) ETFs as well as how illiquidity affects tracking error standard deviation. $ZEROS$ enters significantly with a positive sign indicating that when the underlying index is more illiquid, $TESD$ is higher. The negative coefficient on FI is consistent with the equity premium puzzle. Columns two to four estimate the full model in eqn. (3.12). Column two contains no fixed-effects, column three includes time fixed-effects, and column four additionally includes ETF fixed effects. In column two, increased $ZEROS$, $FEES$, $INDVAR$, DIV, RF, and $SIZE$ are significantly associated with greater tracking error variability. The positive coefficient on $SIZE$ shows that there are diseconomies of scale in tracking ability. AGE obtains a negative coefficient, consistent with more precise tracking ability occurring with more experience. When time fixed-effects are included in column three, all explanatory variables continue to enter significantly and with coefficients that are little changed from column two. Once ETF fixed-effects are additionally included in column four, only $ZEROS$, $INDVAR$ and DIV continue to enter significantly. Their coefficients are similar to their values obtained in columns two and three. $TESD$ also displays ARCH effects as can be seen from the lagged $TESD$, $LTESD$, variable.

Table 3.12 partitions the ETF sample into subsamples of ETFs investing in domestic securities, foreign securities, equities, and fixed income and tests for the determinants of $TESD$. The panel regression model that is estimated is eqn. (3.12) with time fixed-effects. In all subsamples $FEES$, $SIZE$, AGE, and $LTESD$ enter significantly. $FEES$, $SIZE$, and $LTESD$ enter with positive coefficients and AGE enters with a negative coefficient. Following from the results of Christoffersen, et al. (2012) showing that markets are becoming increasingly more integrated over time, the coefficient on AGE should be a larger negative magnitude in the foreign sample than in the domestic sample due to this added reduction in market segmentation. This is what is found. Whereas the coefficient on AGE is -0.002 in the domestic subsample, it is -0.008 in the foreign subsample. $ZEROS$ enters significantly positively in the domestic, foreign, and equities samples. $INDVAR$ enters significantly with a positive sign in the foreign, equities, and fixed income samples. The $LTESD$ coefficients show that, $TESD$ displays stronger ARCH effects in the foreign sample than in the domestic sample and stronger ARCH effects in the equities sample than in the fixed income sample. Overall, Table 3.11 and Table 3.12 show that $TESD$ is a robust measure for market segmentation.

3.5 Conclusion

ETFs persistently trade at a premium to NAV. During the sample period, within-month mean ETF premiums were positive in 89 percent of the months. Further, the fraction of ETFs trading at a within-month mean premium is persistently in excess of the one percent significance level critical value that would exist under the null hypothesis that ETFs are equally likely to trade at a premium as at discount. This is a puzzling result since in the presence of capitalized fees and contingent tax liabilities investors should demand a discount.

This paper shows that market segmentation can explain the puzzling empirical finding that exchange traded funds persistently trade at a premium to NAV. Market segmentation is measured by the standard deviation of tracking errors, the difference between daily ETF NAV returns and daily returns on the index which it aims to replicate. Tracking error standard deviation is positively related to premium level and negatively related to the speed of premium correction. Investors are willing to pay a premium to NAV to obtain the liquidity and diversification benefits that ETFs provide by gaining indirect access to more inaccessible underlying securities. The positive relationship between tracking error standard deviation and premium level is robustly found in ETFs investing in equities and ETFs investing in fixed income as well as in ETFs investing in the U.S. and in ETFs investing in foreign securities. The positive relationship between tracking error standard deviation and premium level is further robust to controlling for investor sentiment effects in the ETF market.

Further tests validate that tracking error standard deviation is a robust measure for market segmentation. These tests confirm that it has the desirable properties of a market segmentation measure. The standard deviation of tracking errors can also be used as a market segmentation measure in other studies where market segmentation or barriers to entry are difficult to measure.

4 Exploiting Closed-end Fund Discounts: The Market May Be Much More Inefficient Than You Thought?

Closed-end funds (CEFs) are investment companies that issue a fixed number of shares and invest the proceeds based on the objective of the fund. Shares of these funds are traded on a stock exchange similarly to common stock and unlike open-end funds cannot be redeemed by the shareholders at their net asset values (NAVs). In efficient and frictionless markets, the share price at which a fund trades must equal its NAV. In reality, however, share prices and NAVs differ. Further, the percentage difference between share prices and NAVs, referred to as the premium, exhibits substantial time-variation. This has puzzled financial economists for over thirty years and a large body of research exists which tries to explain this behavior.

This paper adds to the findings of previous researchers and deepens the CEF discount puzzle by optimally exploiting the information content of historical premiums. First, the mean-reverting behavior of CEFs is examined. Early explanations for why premiums should mean-revert are provided by the noise trader model of De Long, et al. (1990) and the investor sentiment hypothesis of Lee, et al. (1991). Alternatively, premiums should also display rational mean-reversion as a result of time-varying contingent liabilities as evidenced in the findings of Malkiel (1977) and Day, et al. (2011). Mean reversion in CEF premiums is supported in the data. The bias-adjusted speed for mean correction to equilibrium premium levels is 8.6 percent per month, implying an average half-life of 7.7 months. In the presence of mean-reverting premiums, the traditional strategy is to buy the CEFs currently trading at the lowest premiums and to sell the CEFs currently trading at the largest premiums. This naïve model implicitly assumes that the mean-reversion speeds of premiums are constant across funds. This is a very strict restriction that ignores the heterogeneity in mean-reversion speeds and the information contained in the premium history.

This paper uses two new conditioning models of expected returns that exploit the information content of premiums in different ways. The first, a basic mean-reversion (BMR) model, predicts future returns conditioned on current premium alone. This captures the predictive ability of future returns that premiums have been shown to have by Swaminathan (1996), Neal and Wheatley (1998), and Froot and Ramadorai (2008). Thompson (1978) and Pontiff (1995) use similar methods for predicting CEF returns, however, implicitly restricting mean-reversion speeds to be the same across CEFs. The BMR model of expected CEF returns in this paper is unrestricted, taking advantage of differential mean-reversion speeds of fund premiums. The second method predicts future returns in an Augmented Dickey-Fuller (denoted as RADF) type regression, further conditioning on lagged innovations in premiums. Including lagged premium innovations takes advantage of the information contained in premium predictability documented by Day, et al. (2011). If CEF returns are independent of their respective path of premium innovations, then portfolio returns using the BMR model and the RADF model will be similar. Alternatively, portfolio returns using the RADF model will be larger than those using the BMR model if CEF returns are dependent on the path of their premiums.

Naïve benchmark long-short quintile portfolio returns, buying the quintile of CEFs trading at the lowest premiums and selling the quintile of CEFs trading at the highest premiums, yield an annualized mean return of 14.9 percent with a Sharpe ratio of 1.519, which is greater than the 0.170 Sharpe ratio of market returns. There still remains no theory in the extant CEF literature that is able to explain these arbitrage profits. The results further greatly deepen the puzzle by showing that the naïve strategy and previous studies substantially understate the level of inefficiency in the CEF market. The long-short quintile portfolio strategy, using the BMR model, yields annualized mean returns of 17.3 percent with a Sharpe ratio of 1.862. When the RADF model is used, the annualized mean long-short strategy return is 18.2 percent with a Sharpe ratio of 1.918. Since the RADF model yields substantially larger arbitrage profits than the BMR model, the traditional view that expected CEF returns are independent of the path taken by premiums is rejected.

Trading strategy returns are regressed on commonly used risk factors to test if the CEF portfolio returns are an artifact of taking on systematic risks. Returns cannot be explained by the three Fama and French (1993) risk factors, the Carhart (1997) momentum factor and the Pástor and Stambaugh (2003) tradable liquidity factor. The results continue to be robust when only considering subsamples of domestic funds, foreign funds, equities funds, and fixed-income funds. Returns are not driven by systematically buying foreign funds and selling domestic funds to capture a market segmentation premium or by systematically buying equities funds and selling fixed-income funds to capture the equity premium puzzle. Additionally, time period consistency of returns is tested by partitioning the out-of-sample period into two halves. Contrary to what is expected in efficient markets with rational learning, there is no statistically significant difference between mean returns in the first half of the out-of-sample period and mean returns in the second half of the out-of-sample period.

Thompson (1978) is the first to examine if premiums on CEFs are mean-reverting and if premiums have predictive power for future returns of the fund's shares and finds that portfolios of funds trading at discounts outperform the market portfolio. Pontiff (1995) extends this analysis and shows that funds with premiums accrue negative abnormal returns and funds with discounts accrue positive abnormal returns. Lee, et al. (1991) argue that shifting investor sentiment of small investors may explain the puzzle. Small investors create noise in the CEF prices as in the model of De Long, et al. (1990), which creates an arbitrage risk limiting arbitrage effectiveness. Along a different vein, Brickley and Schallheim (1985), Brauer (1988), and Bradley, et al. (2010) show that the open-ending of CEFs benefits shareholders as discounts decline and prices converge to their NAVs. Since relatively few funds are open-ended, Barclay, et al. (1993) test for agency-conflicts with large block holders and find that CEFs with larger block holdings trade at larger discounts. Alternative explanations of the dynamics of CEF premiums are related to managerial ability and market segmentation. Funds with better managerial ability will have better NAV returns. Chay and Trzcinka (1999), Coles, et al. (2000), Johnson, et al. (2006), and Berk and Stanton (2007) provide evidence that CEFs with better NAV returns tend to trade at smaller discounts than those with worse NAV returns. The market segmentation hypothesis argues that investors will choose to trade the more accessible CEFs to gain exposure to the underlying securities, rather than investing directly in the less accessible underlying securities. Bonser-Neal, et al. (1990), Bodurtha, et al. (1995), Gemmill and Thomas (2002), Nishiotis (2004), Cherkes, et al. (2009), Froot and Ramadorai (2008), and Elton, et al. (2013) provide empirical support for the market segmentation hypothesis. This paper adds to the large body of extant literature by optimally exploiting the information content of premiums in new ways to literature. In doing so, I show that inefficiency in the CEF market is much worse than previously thought.

The remainder of this paper is organized as follows. Section 1 presents the empirical methodology used to extract the information content of CEF discounts. Section 2 discusses the data. Section 3 presents empirical results quantifying the magnitude of the CEF discount puzzle. Robustness tests are conducted in Section 4. Concluding remarks are contained in Section 5.

4.1 Empirical Methodology

This section describes the empirical models of expected CEF returns that are employed in the analysis. CEF returns and premiums are respectively calculated as follows:

$$r_{i,t} = \frac{P_{i,t} + D_{i,t}}{P_{i,t-1}} - 1 \tag{4.1}$$

$$prem_{i,t} = p_{i,t} - nav_{i,t} \tag{4.2}$$

where

$$P_{i,t} - \text{market price of the } i'\text{th CEF at time } t$$

$$p_{i,t} - \text{logarithm of market price, } ln\left(P_{i,t}\right)$$

$$D_{i,t} - \text{cash dividend disbursement}$$

$$nav_{i,t} - \text{logarithm of net asset value (NAV)}$$

$$prem_{i,t} - \text{difference between log market price and log net asset value, which is the price premium in relative terms}$$

In this framework, discounts are negative premiums. If the closed end-fund market is weak-form efficient, then the state density of future price is only dependent on the current price. Premiums will not contain information regarding future CEF prices. Contrary to this, if CEF premiums have explanatory power for future CEF prices, then the CEF market is no longer weak-form efficient.

Two new predictive regression models that restrict the information content of premiums in different ways are used in this paper to forecast one-step ahead CEF returns. Evidence against weak-form efficiency showing that premiums contain explanatory power for future returns is provided by Pontiff (1995), Swaminathan (1996), Neal and Wheatley (1998), and Froot and Ramadorai (2008). Ex-ante evidence that premiums should mean revert is provided by Lee, et al. (1991), who show that investor sentiment affects CEF premiums. Since investor sentiment is mean-reverting by definition, premiums will also display mean-reverting behavior which may be used to forecast future premiums and returns. CEFs with poor investor sentiment will trade at smaller premiums than those with better investor sentiment. As sentiment mean-reverts, CEF premiums will mean revert as well. This mean-reverting behavior can be captured by regressing CEF returns on the first lag of premiums

$$r_{i,t} = \alpha_i + \beta_i prem_{i,t-1} + \varepsilon i, t \tag{4.3a}$$

$$\mathbf{E}_t \left[r_{i,t+1} \right] = \widehat{\alpha}_i + \widehat{\beta}_i prem_{i,t} \tag{4.3b}$$

where $\mathbf{E}_t [\cdot]$ is the mathematical expectation operator, conditional on the time t information set, and $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ are regression parameters estimated using data from the first observation in the sample up to time t. Eqns. (4.3a,b) differ importantly from the methodology that Thompson (1978) and Pontiff (1995) use to forecast expected CEF returns based on lagged premiums. Both authors only consider the sign of the premium. Secondly, these authors implicitly assume that $\alpha_i = \alpha$ and $\beta_i = -1$ such that CEFs trading at the smallest premiums are expected to have the highest returns and CEFs trading at the largest premiums are expected to have the lowest returns. By using returns as the dependent variable and by not restricting α_i and β_i, eqns. (4.3a,b) should result in better forecasts of returns based on the sample of data.

Note, however, that eqns. (4.3a,b) continue to neglect the information content that the history of premiums may have. Starks, et al. (2006) show that there is tax-loss selling patterns in municipal bond CEFs. Day, et al. (2011) further provide evidence that CEF premiums display predictable patterns in response to dividend disbursements by funds. Premiums tend to be smallest immediately before a distribution since this is the time that investors' contingent tax liability is greatest. Following disbursement, premiums increase as a result of the diminished tax liability. To account for the information content of possible patterns in premiums and premium innovations, an Augmented Dickey-Fuller (RADF) model of CEF returns is estimated as follows:

$$r_{i,t} = \alpha_i + \beta_i prem_{i,t-1} + \sum_{j=1}^{k_t} \gamma_{i,j} \triangle prem_{i,t-j} + \varepsilon_{i,t} \tag{4.4a}$$

$$\mathbf{E}_t \left[r_{i,t+1} \right] = \widehat{\alpha}_i + \widehat{\beta}_i prem_{i,t} + \sum_{j=1}^{k_t} \widehat{\gamma}_{i,j} \triangle prem_{i,t-j+1} \tag{4.4b}$$

where $\triangle$ denotes the difference operator. The lag length k_t is optimally chosen following the procedure suggested by Campbell and Perron (1991), starting at $k_t = 3$ and reducing the number of lags until the longest lag is statistically significant at the one percent level. Now, expected $t+1$ returns are not only dependent on premiums at time t, but also dependent on the history of premium innovations from time $t - k_t$ to time t.

The return differential between a trading strategy using eqns. (4.4a,b) and (4.3a,b) can also be interpreted as a test of the validity of the traditional assumption that for CEFs only the lagged premium contains explanatory power for returns. If portfolio returns using eqns. (4.3a,b) are similar to portfolio returns using eqns. (4.4a,b), then the traditional assumption holds up. If portfolio returns using eqns. (4.4a,b) are larger than those from using eqns. (4.3a,b), then the traditional assumption can be rejected in favor of the alternative hypothesis that CEF returns are not independent of premium path. Those are the hypotheses that I test. Eqns. (4.3a,b) and (4.4a,b) are referred to as the basic mean-reversion (BMR) model and the RADF model for the remainder of the paper.

4.2 Data

Monthly data are compiled from four different data sources. Data on CEF share prices, total returns, trading volumes, and shares outstanding is obtained from the CRSP monthly stock file database. There are 693 CEFs in the CRSP universe. CEFs incorporated outside of the United States are excluded from the sample. End-of-month fund net asset values are obtained from Bloomberg. Not all CEF observations in CRSP have an accompanying NAV observation available in Bloomberg. The final sample consists of the intersection of the two databases which leaves 377 CEFs that trade in the U.S. covering the August 1984 to December 2011 period. Missing values for CEF returns are imputed with the sample mean of that CEF's return time series[1]. Data on the three Fama and French (1993) factors, as well as the Carhart (1997) momentum factor, are obtained from

[1]Results are unchanged when missing values are imputed with zero

Kenneth French's website. Data on the Pástor and Stambaugh (2003) tradable liquidity factor is obtained from Ľuboš Pástor's website.

CEF fund type classifications are obtained from Morningstar. Table 4.1 presents the cross-section of fund categories and types. Panel A shows that 61.7 percent of the CEFs are categorized as domestic funds, 21.1 percent are categorized as foreign funds, and the remaining 17.2 percent have a miscellaneous categorization. Of those CEFs that invest domestically, 15.5 percent invest in domestic equities and 84.5 percent invest in domestic fixed income securities. Of those CEFs that invest internationally, 79.1 percent invest in foreign equities and 20.9 percent invest in foreign fixed income securities. The last two columns present a snapshot of the cross section of sample CEFs in the latest sample year, 2011. In 2011, the mean market value of equity (MVE) was \$370 million for domestic CEFs, \$336 million for foreign CEFs, and \$140 million for miscellaneous CEFs. There were 192 domestic CEFs, 29 of which invested in equities and 163 of which invested in fixed income securities. 39 funds invested in foreign equities and 11 funds invested in foreign fixed income securities. The remaining 17 funds in the sample in 2011 invested in the miscellaneous category.

Figure 4.1 plots the time series of the number of CEFs contemporaneously included in the sample in the top panel and the time series of total assets under management of the sample funds in the bottom panel. Total sample assets under management for CEFs contemporaneously in the sample increases from \$0.07 billion in 1984 to a high of \$109 billion in 2007.

Figure 4.2 plots the distribution of CEF premium observations for the sample. CEFs generally trade at a discount. The distribution appears to be bi-modal with a sample mean premium of -4 percent and sample standard deviation of 22 percent. Fund type appears to be random in the cluster of premiums centered at -76 percent. There is not a specific fund type that tends to trade at such a deep discount. CEFs that trade at a premium to NAV tend to be fixed-income funds, funds that invest in natural resources, and funds that invest internationally. That these fund types predominantly trade at premiums is consistent with the model of Cherkes, et al. (2009) where investors trade in the more easily accessible CEFs rather than trade in the less accessible underlying assets directly.

4.3 Empirical Results

4.3.1 CEF Trading Strategy Implementation

When implementing the BMR and RADF models based on eqns. (4.3a,b) and (4.4a,b), approximately the first one-third of the sample period is used as the base estimation period and the remaining two-thirds of the sample is used as the out-of-sample test period. The first out-of-sample predicted CEF return is February 1998. CEFs are required to have existed for at least 120 months prior to entering the sample and being used in the estimations of eqns. (4.3a,b) and (4.4a,b). Expected returns are estimated in a cumulative rolling regression method. Since time $t+1$ expected returns are estimated based only on information available at time t, expected returns are immune to look-ahead bias. After time $t+1$ expected returns are estimated, CEFs are sorted into five equally weighted portfolios of CEFs based on expected returns. A long-short portfolio is formed by buying the portfolio with the highest expected return and shorting the portfolio with the lowest expected return. Three different trading strategy returns are estimated; one for each of the two expected return models, and as a benchmark case, the traditional naïve strategy of buying the portfolio of CEFs that trade at the lowest premiums and selling the portfolio of CEFs that trade at the highest premiums is estimated.

4.3.2 Mean-Reversion in CEF Premiums

Augmented Dickey-Fuller regressions are used to test for mean reversion and to estimate the speed of mean reversion for each CEF individually. Histograms of estimated mean reversion coefficients and tau-statistics to test for mean reversion in CEF premiums and are presented in the top and bottom panels of Figure 4.3, respectively. The mean of the estimated mean reversion parameter β is -0.138. It is well-known that this parameter estimate is downward biased. To give an estimate of the bias, I simulate time series under the null hypothesis of a random walk with 100 observations, and estimate the β. With 10,000 replications, the average β is estimated to be -0.052, which is the estimated bias of the mean reversion speed under the null[2]. This gives the average bias-adjusted parameter for the sample of CEFs to be -0.086 $(-0.138+0.052)$. This implies an average half-life of 7.7 $(= ln(0.5)/ln(1-0.086))$ months for mean reversion in CEF premiums, a very fast speed. From the top panel of Figure 4.3, a wide dispersion of mean-reversion coefficients can be observed, indicating that the naïve strategy ignores important heterogeneity in mean-reversion speeds. Under the null hypothesis of no mean reversion, the 5 percent critical value for the sample size of 100 is -2.89 (see Fuller, 1976, p.369). From the bottom panel of Figure 4.3, the null hypothesis can be rejected at the 5 percent significance level in favor of mean reversion in fund premium for a substantial number of CEFs[3].

Figure 4.4 plots histograms of mean monthly returns across CEFs. Mean returns for the full sample are plotted in Panel A. Panels B and C plot mean monthly returns for CEFs that primarily invest in equities and fixed-income securities, respectively. Unconditionally, the annualized mean return for equities CEFs is 10.4 percent and the annualized mean return for fixed-income CEFs is 7.6 percent.

4.3.3 CEF Trading Strategy Returns

Table 4.2 presents portfolio performance for the benchmark naïve trading strategy that buys the quintile portfolio of CEFs trading at the lowest premium and sells the quintile portfolio of CEFs trading at the highest premium with monthly rebalancing. Results using the full sample are presented in Panel A. The full sample annualized mean return of the naïve strategy is 14.9 percent and is statistically significant at the one percent level. The Sharpe ratio of the arbitrage portfolio is 1.519, which is larger than the market Sharpe ratio of 0.170 over the same period. Trading strategy returns are

[2] Balvers, et al. (2000) suggest estimating the bias under the alternative of mean reversion. I choose not to pursue such a strategy because that will require running a separate set of simulations for each of the CEFs in the sample. The difference is not expected to be large.

[3] I acknowledge that ADF-type tests have very low power to reject the null hypothesis of a random walk in favor of the alternative of mean reversion in small samples.

generated symmetrically by both the long and short portfolios. This return from the naïve strategy is similar to the strategy returns in Pontiff (1995). Both the long and the short legs of the arbitrage portfolio contribute roughly symmetrically. While the mean return on the portfolio of CEFs trading at the lowest premium outperforms the market by a statistically significant 9.3 percent, the mean return on the portfolio of CEFs trading at the highest premium underperforms the market and is not significantly different from zero.

The PTO, MVE, STO, and DVOL columns give statistics on portfolio turnover, portfolio mean CEF market value of equity, portfolio mean CEF share turnover, and portfolio mean CEF dollar trading volume. Portfolio positions turnover relatively infrequently with the long-short portfolio turning over at an annualized rate of 2.335 times. Mean CEF market-cap traded is \$382.468 million, annualized mean share turnover is 63.8 percent, and annualized mean CEF dollar volume traded is \$223.706 million. While CEF share turnover and dollar trading volume appear small, they coincide with the fourth and fifth deciles of NYSE stocks over the same sample period (not reported). In practice, there would have been sufficient liquidity for this trading strategy to have been a tradable one. The last column of Table 4.2 contains mean Dickey-Fuller mean-reversion parameter estimates (MRP), estimated in a cumulative rolling manner, for CEFs in each portfolio. Whereas the mean mean-reversion parameter for the full sample of CEFs is -0.117, it is -0.108 for the Q5-Q1 long-short portfolio. Given the estimated bias of 0.052 under the null hypothesis of a random walk reported in section 4.3.2, these mean-reversion parameters correspond to a premium half-life of 10.32 months for the full sample of CEFs and a mean-reversion speed of 12.03 months for CEFs in the Q5-Q1 long-short portfolio. The slower mean-reversion speeds of CEFs in the Q5-Q1 portfolio provide evidence that neglecting heterogeneity in mean-reversion parameters may result in suboptimal portfolio allocation.

Naïve strategy returns using domestic and foreign subsamples of CEFs are presented in Panels B and C, respectively. The mean return for the long-short strategy is 12.1 percent in the domestic CEF universe. Both the long and short portfolios continue to contribute roughly symmetrically to strategy returns. Trading returns are slightly larger in the foreign CEF subsample with the annualized long-short mean return being 15.4 percent. While the mean return in the foreign subsample is higher, its Sharpe ratio is only 0.857 whereas the Sharpe ratio obtained in the domestic subsample is 1.506. Mean MRPs for the Q5-Q1 portfolios in the domestic and foreign subsamples are similar to those in the full sample case. Portfolio turnovers, mean CEF share turnovers, and mean CEF dollar trading volume are greater in the foreign subsample than in the domestic subsample.

Table 4.3 presents mean returns from the long-short strategies discussed in Section 4.3.1 using the full sample of CEFs and the BMR and RADF models to forecast expected CEF returns. The annualized mean return from the BMR long-short strategy is 17.3 percent. This is 2.4 percentage points greater than the benchmark strategy, indicating that important information about CEF return dynamics is lost by not allowing the coefficients in eqns. (4.3a,b) to be freely estimated. The Sharpe ratio for the BMR strategy is 1.862. Similar to the benchmark strategy, the long and short positions contribute roughly symmetrically to the mean return. Possible short sale restrictions cannot explain the magnitude of inefficiency as evidenced by the Q5-MRKT portfolio. The mean return from this strategy is 9.8 percent per annum and the Sharpe ratio is 0.795. In contrast to the naïve strategy, the mean Dickey-Fuller mean-reversion speed of CEFs in the Q5-Q1 portfolio is -0.154 (a half-life of 4.14 months), a much quicker mean reversion speed. Taking into account the heterogeneity in CEF mean-reversion speeds substantially improves trading strategy returns over the naïve model, which does not take into account mean-reversion speed heterogeneity.

Portfolio mean returns from the trading strategy that uses the RADF model of expected returns are presented in Panel B. If the premium history beyond the first lagged premium contains no explanatory power for returns, then mean returns in Panel B should match those in Panel A. The annualized mean return from the long-short strategy is 18.2 percent. The larger RADF returns indicates that inefficiency in the CEF market is more severe than previously documented and that the histories of premiums have explanatory power for returns. Expected CEF prices are not independent of the path that its premiums have taken. The Sharpe ratio of the Q5-Q1 RADF strategy is 1.918. Similarly to the naïve model and the BMR model, the long and short portfolios contribute symmetrically to strategy returns. The long portfolio minus market portfolio strategy yields an annualized mean return of 10.7 percent providing further evidence that short sale restrictions are not the source of predictable trading strategy returns. The mean Dickey-Fuller mean-reversion speed of CEFs in the Q5-Q1 portfolio is -0.132 (a half-life of 4.9 months) providing evidence that the RADF model also optimally takes into account heterogeneous MRPs. Since the Q5-Q1 portfolio returns are larger using the RADF model than when using the BMR model, and since the traded CEF mean-reversion speeds are similar, the large increase in trading strategy returns is the result of incorporating the information content of the historic path of premiums.

Figures 4.5 plots the monthly returns from the long-short naïve benchmark strategy in the top panel and the trading returns using the RADF model of expected CEF returns in the bottom panel. The realized strategy returns appear to be randomly distributed over time. Large return outliers are not present in the return time series. Therefore, there is no evidence that a peso problem could explain the consistent arbitrage returns. It is interesting to note that during the 2001 recession following the tech-bubble crash and during the recent 2007-2009 financial crisis, both the benchmark strategy and the RADF strategy would have provided a good hedge against generally falling markets. In an efficient market, an investor should not be able to obtain such predictable returns.

Table 4.4 presents realized mean returns by ex-ante expected return-sorted CEF quintile in Panel A and tests for a monotonic relationship between mean trading returns and mean ex-ante expected return estimated from the RADF model in Panel B. Only mean quintile returns for quintiles one and two are not significantly different from zero. The first row in Panel A shows that the mean number of CEFs per quintile is approximately 25. Quintiles are well diversified and trading returns are not being driven by a small subset of CEFs. Two tests for monotonicity in returns are conducted: one parametric and one non-parametric. The parametric test is a regression of mean quintile return on a constant and a trend variable ascending from one to five. The non-parametric test is Kendall's rank correlation test[4]. Kendall's tau is bound between -1 and 1. If the rankings of two variables, in this case trading mean returns and forecasted returns, agree in ascending ranking completely, then Kendall's tau will equal 1. If they have a completely reversed ranking relationship, then Kendall's tau will equal -1. Both tests of monotonic trend indicate that portfolio returns are significantly monotonically higher for CEF quintiles with higher forecasted returns. The trend test indicates that an investor earns an annualized 4.3 percentage points more in expected return by moving to an adjacent quintile with greater forecasted return.

Since parameters are required to be estimated in the BMR and RADF models, their forecasting ability should be increasing in the time-series length of closed-end funds because a higher precision in parameter estimation can be obtained with more observations. Table 4.5 presents mean returns for the naïve, BMR, and RADF trading strategies conditioned on the minimum number of observations a CEF is required to have prior to entering the sample. The RADF model outperforms both the BMR and naïve models when the minimum number of CEF observations is greater than or equal to 120 months. Similarly, the BMR model outperforms the naïve model when the minimum number of observations required for a CEF to enter the sample is greater than or equal to 120 months. When the required number of observations for a CEF to enter the sample is 36 months or 60 months the naïve model outperforms both the BMR model and the RADF model. Even with these short in-sample periods the RADF model obtains mean returns that are approximately equal to those of the naïve model, however. That the forecasting performance of the BMR and RADF models improves relative to the naïve strategy as the minimum in-sample period lengthens indicates that the models are asymptotic in nature. In small samples, there exists a trade-off between proper model specification and estimation precision. How well the parametric model performs relative to the non-parametric one in an actual sample is an empirical question.

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[4]See Kendall (1938) for test details.

4.3.4 Risk-Adjusted Returns

This subsection tests if the trading returns reported in the previous section could be the result of taking on greater systematic risks. In the absence of arbitrage opportunities, risk-discounted portfolio returns will have a price of zero

$$\mathbf{E}\left[m_{t+1} r^e_{p,t+1}\right] = 0 \tag{4.5}$$

where $r^e_{p,t+1}$ is the portfolio excess return and m_{t+1} is the pricing kernel. m_{t+1} is restricted to be linear in k factors

$$m_{t+1} = 1 - \sum_{i=1}^{k} b_i f_{i,t+1} \tag{4.6}$$

where $b_i = \mathbf{CV}\left[f_{i,t+1}, r^e_{p,t+1}\right] / \mathbf{V}\left[f_{i,t+1}\right]$, $\mathbf{CV}[\cdot]$ is the covariance operator, and $\mathbf{V}[\cdot]$ is the variance operator. Eqn. (4.6) implies a beta pricing model for expected excess returns. The pricing kernel in eqn. (4.6) is taken in this paper to be the factor model of Fama and French (1993) augmented with the Carhart (1997) winners-minus-losers (WML) factor and the Pástor and Stambaugh (2003) tradable liquidity (LIQ) factor (hereafter referred to as the FFCPS model)

$$\begin{aligned} m_{t+1} = 1 &- b_1 r^e_{MRKT,t+1} - b_2 r_{SMB,t+1} - b_3 r_{HML,t+1} \\ &- b4 r_{WML,t+1} - b5 r_{LIQ,t+1} \end{aligned} \tag{4.7}$$

r^e_{MRKT} is the monthly excess return of the market portfolio over the risk-free rate, r_{SMB} is the monthly return on the small-minus-big (SMB) portfolio, r_{HML} is the monthly return on the high-minus-low (HML) book-to-market portfolio, r_{WML} is the monthly return on the WML portfolio, and r_{LIQ} is the monthly return on the LIQ portfolio. Table 4.6

presents results from regressing naïve trading strategy returns on the FFCPS factors:

$$r^e_{p,t} = \alpha_p + \beta_{p,1} r^e_{MRKT,t} + \beta_{p,2} r_{SMB,t} + \beta_{p,3} r_{HML,t} + \beta_{p,4} r_{WML,t} + \beta_{p,5} r_{LIQ,t} + \varepsilon_{p,t} \tag{4.8}$$

Panels A, B and C of Table 4.6 display results for the full sample of CEFs, the domestic sample, and the foreign sample, respectively. The alphas (i.e., the risk-adjusted returns) for the long-short strategy are 14.8 percent, 11.9 percent, and 16.0 percent per annum for the full sample, the domestic sample, and the foreign sample, respectively, each of which is statistically significant at the one percent level. The alphas are approximately equal to the mean returns, indicating that the FFCPS factors collectively have close to zero explanatory power for the naïve trading strategy returns. In all three panels, Q1 and Q5 returns load positively on the MRKT factor, SMB factor, and LIQ factor. Q1 and Q5 returns load negatively on the WML factor in all three panels. Q1 returns load positively on the HML factor in the full sample and in the domestic sample. A significant factor loading on the HML factor is only obtained for Q5 returns in the full sample and it is negative. The positive factor loadings for the Q1 and Q5 portfolios indicates that the naïve strategy tends to trade CEFs holding smaller securities, recent losers, and securities with greater liquidity risk. Once the arbitrage portfolio is formed, none of the factors obtain consistently significant loadings across samples.

Abnormal return results from long-short strategies using the optimal RADF model are presented in Panel A of Table 4.7. In Panel A, the annualized arbitrage portfolio alpha (or abnormal return) is 17.4 percent, which is highly significant and is approximately equal to the unadjusted mean return reported in Table 4.3 Panel B. Furthermore, while the mean return for the short quintile portfolio (Q1) reported in Table 4.3 Panel B is insignificantly different from zero, the risk-adjusted return for this portfolio is -7.4 percent, which is significant at the one percent level. These results further provide evidence against the view that only the first lagged premium contains explanatory power for CEF returns. Portfolio alphas using the sample of domestic CEFs are presented in Panel B and alphas using the sample of foreign CEFs are presented in Panel C. The annualized alpha for the long-short strategy in the domestic sample is 16.1 percent and the annualized alpha for the arbitrage portfolio in the foreign sample of CEFs is 18.8 percent. Similarly to the benchmark strategy, in all three panels Q1 and Q5 returns load positively on the MRKT factor and load negatively on the WML factor. In the full sample and in the domestic sample, Q1 and Q5 returns load positively on the LIQ factor. Once the arbitrage portfolio is formed, none of the factors obtain consistently significant loadings across samples. In summary, the large arbitrage trading strategy returns cannot be explained by commonly used risk factors.

4.4 Robustness of the Findings

4.4.1 Equity Premium Puzzle Robustness

Since fixed-income securities are in general less risky with lower expected returns than equities securities, the long-short portfolio returns may be an artifact of the equity premium puzzle by systematically buying equities CEFs and selling fixed-income CEFs. Table 4.8 presents portfolio alphas, obtained from regressing portfolio returns on the FFCPS factors, when CEFs are partitioned into a subsample of equities funds and a subsample of fixed-income funds. Only returns from the strategy using the optimal RADF model are presented to conserve space. The annualized abnormal long-short portfolio return for the equities subsample is 15.4 percent in Panel A. Q1, Q5, and Long-short portfolio returns have significantly positive MRKT betas. MRKT betas for the Q1 and Q5 portfolios are 1.010 and 1.128, respectively. Panel B presents portfolio abnormal returns in the fixed-income subsample. The annualized alpha for the long-short strategy is 17.2 percent. Consistent with fixed-income securities being less variable than equities, Q1 and Q5 returns have MRKT betas of 0.171 and 0.091 (insignificantly different from zero) which are less than those obtained for equities CEFs. While portfolio alphas are slightly larger in the fixed-income funds case, the trading returns cannot be attributed to biased holdings in equities or fixed-income CEFs.

4.4.2 Sup-period Robustness

That the CEF discount continues to be exploitable is puzzling since it was first documented more than thirty years ago. Table 4.9 formally tests the sub-period consistency of returns by partitioning the sample into two subsamples of equal observations. Trading return results are those obtained from using the RADF model. Given that investors were more fully aware of the potential returns that could be obtained by trading in CEFs in the second half of the sample, mean returns should be lower in the second half of the sample if the CEF market is efficient with rational learning. Contrary to this, however, there is no statistically significant difference between subsample mean returns. The annualized mean return for the long-short strategy in the first half of the sample is 18.8 percent and in the second half of the sample the respective annualized mean long-short return is 17.5 percent. Q5 mean returns are statistically significant from zero in both halves of the sample and in both halves of the sample Q1 returns are insignificantly different from zero. The difference in returns between the first half of the sample and the second half is insignificantly different from zero in all cases. The Q5-MRKT returns are also statistically greater than zero and do not display a tendency to diminish over time. This evidence that such large arbitrage returns remain unexploited substantially deepens the CEF discount puzzle.

4.4.3 Holding Period Robustness

Table 4.10 presents cumulative abnormal portfolio returns, for holding periods of three, six, nine, twelve, eighteen, and twenty-four months. I test how long-lived the information content of premiums and premium innovations is. To conserve space, only FFCPS alphas are presented for trading strategy returns that use the RADF model. Even after twenty-four months there is evidence of return continuation in the arbitrage portfolio. Whereas the long-short mean return for a one-month holding period is 1.5 percent, the mean cumulative return for the twenty-four-month holding period is 10.2 percent. There is evidence of return reversal at the nine-month horizon. Mean cumulative monthly returns decrease from 2.0 percent for a six-month holding period to 1.2 percent (insignificantly different from zero) for a nine-month holding period. However, that returns remain significant with a holding period of twenty-four months (10.2 percent with a t-statistic of 5.338) indicates a high level of inefficiency.

4.4.4 Closed-End Fund Robustness

As a further test of efficiency in the CEF market, this paper tests for momentum effects. Given how long lasting the information content of premiums is, there may be momentum effects in the CEF market. Momentum appears in a wide range of asset classes. Jegadeesh and Titman (1993) document momentum effects for equities. Momentum spillovers from the equities market to corporate bonds are found by Gebhardt, et al. (2005). Similarly, Okunev and White (2003) and Menkhoff, et al. (2012) report momentum effects for currencies. Asness, et al. (2013) provide comprehensive evidence of momentum effects for a wide range of asset classes, including providing evidence for commodities. Since CEF premiums mean-revert, it is not immediately obvious if momentum effects will be present. If market prices and NAVs have similar variability, then momentum may exist. Alternatively, if market prices are much more variable than NAVs, then the effects of mean-reversion in fund premiums can dominate and momentum effects are not likely.

Table 4.11 presents CEF returns from a momentum strategy that buys the quintile portfolio of CEFs with the highest previous period return and sells the quintile portfolio of CEFs with the lowest previous period return. Panel A presents returns from a simple random walk with drift strategy, as a benchmark case. Expected returns in this random walk case are modeled as

$$\mathbf{E}\left[r_{i,t+1}\right] = \left(t - t_{i,1} + 1\right)^{-1} \sum_{j=t_{i,1}}^{t} r_{i,j} \tag{4.9}$$

where $t_{i,1}$ is the first observation of the sample for the i'th CEF. Eqn. (4.9) models CEF expected return as the cumulative rolling mean return. CEFs are sorted into portfolios based on expected return and the long-short strategy is formed by buying the quintile portfolio with the highest expected return and selling the quintile portfolio with the lowest expected return. Annualized mean returns for portfolio sorts are roughly the same as market returns, as would be expected. Mean returns produced by the long-short strategy are insignificantly different from zero.

Mean momentum strategy returns are presented in Panel B, where CEFs are sorted into quintile portfolios based on their mean returns over the past $h \in \{3, 6, 9, 12\}$ months and held for the same number of months. The annualized mean return for the long-short momentum portfolio is never significantly higher than zero for all holding periods. Returns in the portfolios of winners and losers tend to cancel each other out as is evidenced by the portfolio returns that buys the past winners and sells the market portfolio. Evidence provided in Table 4.11 suggests that momentum effects do not seem to exist in the CEF market. This is to be expected if premiums mean revert due to risky arbitrage.

4.5 Conclusion

This paper provides new evidence on the magnitude of inefficiency in the closed-end fund market that greatly deepens the discount puzzle. My results relieve the traditional imposed assumption that only lagged premium has explanatory power for future CEF returns in favor of modeling CEF returns as being dependent on the optimally chosen history of premiums. A long-short trading strategy is formed that buys the quintile of CEFs with the highest expected returns and sells the quintile of CEFs with the lowest expected returns. Expected returns are estimated using two new methods that exploit different aspects of the information content of premiums. The first conditions returns on lagged discounts alone (BMR model) to capture simple mean reversion and the second is an ADF style model of returns which conditions CEF returns on lagged innovations in premiums (RADF model) to capture the information content of possible patterns in premium dynamics.

Annualized arbitrage trading strategy returns are 17.3 percent for the BMR model and 18.2 percent for the RADF model, which are larger than the 14.9 percent naÃŕve CEF trading strategy return. Since portfolio returns using the RADF model are larger than those using the BMR model, the traditional view of modeling expected CEF returns dependent only on current premium is rejected in favor of modeling expected returns as being dependent on premium path. Sharpe ratios for the strategies using the BMR and RADF models are 1.862 and 1.918, respectively, which are much larger than the Sharpe ratio of 0.170 for market returns and larger than the Sharpe ratio of 1.519 for the naïve strategy returns.

In contrast to what would be expected in an efficient market with rational learning, returns are not time period sensitive. There is no statistically significant difference between mean returns in the first half of the sample and the second half. A number of robustness tests are conducted to test if the large CEF trading strategy returns result from taking on other known market risks. Arbitrage trading returns cannot be explained by commonly used risk factors. Results are robust to only considering subsamples of domestic funds and foreign funds, indicating that the CEF strategy simply does not capture a market segmentation premium. Results are also robust to only considering subsamples of equities funds and fixed-income funds, providing evidence that CEF strategy returns are not a result of selling fixed-income and buying equities to capture the equity premium puzzle. This paper's findings indicate that inefficiency in the CEF market is far worse than previously thought and deserves further research attention.

Appendix A The Kalman Filter Recursions

The general state-space model (SSM) consists of the following observation and transition equations

$$y_{i,t} = \mathbf{H}_{i,t} z_{i,t} + \mathbf{G}_{i,t} x_{i,t} + v_{i,t} \tag{A1}$$

$$z_{i,t} = \mathbf{B}_{i,t-1} z_{i,t-1} + \mathbf{F}_{i,t-1} x_{i,t-1} + \omega_{i,t} \tag{A2}$$

Eq. (A1) is the observation equation and eq. (A2) is the transition equation. $z_{i,t}$ is an $(N \times 1)$ state vector, $y_{i,t}$ is a $(K \times 1)$ vector observed time series, $\mathbf{H}_{i,t}$ is a $(K \times N)$ measurement matrix, $\mathbf{G}_{i,t}$ is a $(K \times M)$ input matrix for the observation equation, $\mathbf{B}_{i,t}$ is an $(N \times N)$ transition matrix, $v_{i,t}$ is a $(K \times 1)$ vector of noise, $\mathbf{F}_{i,t}$ is an $(N \times M)$ input matrix for the transition equation, $x_{i,t}$ is an $(M \times 1)$ vector of observable instruments, and $\omega_{i,t}$ is an $(N \times 1)$ vector of noise. Both $v_{i,t}$ and $\omega_{i,t}$ are assumed to be normally distributed random variables with $v_{i,t} \sim N\left(0, \sigma_{v_i}^2\right)$ and $\omega_{i,t} \sim N\left(0, \Sigma_{\omega_i}\right)$. Σ_{ω_i} is a diagonal matrix. Additionally, the initial state is normally distributed $z_{i,0} \sim N\left(\overline{z}_{i,0}, \Sigma_0\right)$. Although normality is assumed, it is still possible to justify the Kalman filter recursions if this is not the case[1]. In eqn. (2.1), $y_{i,t} = r_{i,t}$, $z_{i,t} = \left(\alpha_{i,t}, \boldsymbol{\beta}'_{i,t}\right)'$, $\mathbf{H}_{i,t} = (1, r_{m,t})'$, $\mathbf{B}_i = \mathbf{I}_2$, and $\mathbf{G}_i = \mathbf{F}_i = \mathbf{0}$. In eqn. (2.4), $y_{i,t} = \widehat{e}_{i,t}$, $z_{i,t} = z_{i,t}$, $\mathbf{H}_{i,t} = r_{I,t}^{(i)}$, $\mathbf{B}_i = 1$, and $\mathbf{G}_i = \mathbf{F}_i = \mathbf{0}$.

The following additional notation is used in the Kalman Filter recursions, where $s < t$,

$$\begin{aligned} z_{t|s} &= \mathbf{E}\left(z_t | y_1, y_2, \ldots, y_s\right) \\ \Sigma_z\left(t|s\right) &= \mathbf{V}\left(z_t | y_1, y_2, \ldots, y_s\right) \\ y_{t|s} &= \mathbf{E}\left(y_t | y_1, y_2, \ldots, y_s\right) \\ \Sigma_y\left(t|s\right) &= \mathbf{V}\left(y_t | y_1, y_2, \ldots, y_s\right) \end{aligned}$$

Within the general SSM framework, eqns. (2.1) and (2.4) are estimated with the Kalman filter recursions with $\mathbf{B}$, $\mathbf{F}$, and $\mathbf{G}$ time invariant. The recursions consist of an

[1]See Lütkepohl (2005), ch. 18.

initialization step, prediction step, and correction step, which are given below.

$$Initialization:$$

$$z_{i,0|0} = \overline{z}_{i,0}$$

$$\Sigma_{i,z} = (0|0) = \Sigma_{i,z}(0)$$

$$Prediction\ Step\ (1 \leq t \leq T):$$

$$z_{i,t|t-1} = \mathbf{B}_i z_{i,t-1|t-1}$$

$$\Sigma_{i,z}(t|t-1) = \mathbf{B}_i \Sigma_{i,z}(t-1|t-1)\mathbf{B}_i' + \Sigma_{\omega_i}$$

$$y_{i,t|t-1} = \mathbf{H}_{i,t} z_{i,t|t-1}$$

$$\Sigma_{i,y}(t|t-1) = \mathbf{H}_{i,t}\Sigma_{i,z}(t|t-1)\mathbf{H}_{i,t}' + \sigma_{v_i}^2$$

$$Correction\ Step\ (1 \leq t \leq T):$$

$$\mathbf{P}_{i,t} = \Sigma_{i,z}(t|t-1)\mathbf{H}_{i,t}'\Sigma_{i,y}(t|t-1)^{-1}$$

$$z_{i,t|t} = z_{i,t|t-1} + \mathbf{P}_{i,t}\left(y_{i,t} - y_{i,t|t-1}\right)$$

$$\Sigma_{i,z}(t|t) = \Sigma_{i,z}(t|t-1) - \mathbf{P}_{i,t}\Sigma_{i,y}(t|t-1)\mathbf{P}_{i,t}'$$

Appendix B The Likelihood Function

To begin the Kalman filter recursions, the initial parameter vector $\boldsymbol{\theta}_i = \left(\sigma^2_{v_i}, \boldsymbol{\iota}'\Sigma_{\omega_i}, \overline{z}_{i,0}, vech\left(\Sigma_{i,z}\left(0\right)\right)'\right)'$ is required. $\boldsymbol{\iota}$ is the unit vector and $vech$ is the matrix operator that stacks only the elements on and below the main diagonal of a square matrix. $\boldsymbol{\theta}_i$ is estimated by maximizing the constrained log-likelihood function,

$$\begin{aligned} lnL\left(\boldsymbol{\theta}_i|y_i\right) = &-\frac{T}{2}ln\left(2\pi\right) - \frac{1}{2}\sum_{t=1}^{T}\left|\Sigma_{i,y}\left(t|t-1\right)\right| \\ &-\frac{1}{2}\sum_{t=1}^{T}\left(y_{i,t} - y_{i,t|t-1}\right)^2/\Sigma_{i,y}\left(t|t-1\right) \end{aligned} \tag{B1}$$

where $\left|\Sigma_{i,y}\left(t|t-1\right)\right|$ is the determinant of $\Sigma_{i,y}\left(t|t-1\right)$. The constraints are that $\sigma^2_{v_i}$, must be greater than or equal to zero and that the main diagonal elements of Σ_{ω_i} and $\Sigma_{i,z}\left(0\right)$ must be greater than or equal to zero. Rather than adding constraints to the optimization problem, the constraints are implicitly imposed by maximizing (B1) over $\tilde{\boldsymbol{\theta}}_i = \left(\lambda_1, \boldsymbol{\lambda}_2', \overline{z}_{i,0}, vech\left(\Sigma_{i,z}\left(0\right)\right)'\right)'$. λ_1 is a scalar, $\boldsymbol{\lambda}_2$ is a $(N \times 1)$ vector, $\overline{z}_{i,0}$ is a $(N \times 1)$ vector, and $vech\left(\Sigma_{i,z}\left(0\right)\right)$ is a $\left(\left[N \cdot (N+1)\right]/2 \times 1\right)$ vector. The optimum parameters in $\boldsymbol{\theta}_i$ are taken to be $\sigma^2_{v_i} = \sqrt{\left(\lambda_1\right)^2}$, $\Sigma_{\omega_i} = \sqrt{diag\left(\boldsymbol{\lambda}_2 \circ \boldsymbol{\lambda}_2\right)}$, $\overline{z}_{i,0}$, and $\Sigma_{i,z}\left(0\right)$ with the absolute value of the main diagonal of $\Sigma_{i,z}\left(0\right)$ replacing its estimated main diagonal. $diag\left(\cdot\right)$ is the operator that transforms a vector into a diagonal matrix with the i'th element of the vector as the ii'th element of the matrix and $\circ$ denotes the Hadamard product.

Eq. (B1) is maximized using the Newton-Raphson method. Starting values for eqn. (2.1) are $\tilde{\boldsymbol{\theta}}_i^{st} = \left(0.001, \boldsymbol{\iota}_2'\left(0.001 \times \mathbf{I}_2\right), \widehat{\boldsymbol{\varphi}}_i, vech\left(\widehat{\Sigma}_{\boldsymbol{\varphi}_i}\right)'\right)'$. $\widehat{\boldsymbol{\varphi}}_i$ is the vector of time-invariant parameter estimates from estimating eqn. (2.1) with OLS. $\widehat{\Sigma}_{\boldsymbol{\varphi}_i}$ is the variance-covariance matrix of the $\widehat{\boldsymbol{\varphi}}_i$ estimator. Starting values for eqn. (2.4) are $\tilde{\boldsymbol{\theta}}_i^{st} = \left(0.001, 0.001, \widehat{\varphi}_i, \widehat{\sigma}^2_{\widehat{\varphi}}\right)'$. $\widehat{\varphi}_i$ is the OLS estimate obtained from estimating eqn. (2.4). $\widehat{\sigma}^2_{\widehat{\varphi}}$ is the variance of the estimator $\widehat{\varphi}_i$. Convergence in the objective function is assumed to occur at iteration m when the change in likelihood function value satisfies $\parallel lnL\left(\boldsymbol{\theta}_i|y_i\right)^{(m)} - lnL\left(\boldsymbol{\theta}_i|y_i\right)^{(m-1)} \parallel \leq 1 \times 10^{-9}$, where $\parallel \cdot \parallel$ denotes the Euclidean norm.

All parameters to be optimized are robust to the choice of starting values. The optimum values of $\boldsymbol{\theta}_i$ are used to run through the Kalman filter recursions for the i'th bank.

5 References

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Table 2.1
Summary Statistics

This table presents summary statistics for the daily sample of financial firms in panel A and the CRSP sample of stocks in panel B. PRICE is stock price, RET, is monthly stock total return, MVE is market value of equity (in billions), BIR is the bank index return, $\widehat{z}_{t|t}$ is the coefficient estimate in eqn. (2.4), $FC_t^{(i)}$ is the contribution of bank i to financial contagion multiplied by 100, and FC_t is the financial contagion estimate obtained from eqn. (2.8). The bank sample in Panel A covers the period January 1, 1960 to December 31, 2012. Monthly stock and factor summary statistics are presented in panel B. VOL is monthly trading volume (in millions), MRKT is the excess market factor portfolio return, SMB is the small minus big factor portfolio return, HML is the high minus low factor portfolio return, MOM is the momentum factor portfolio return, LIQ is the tradable liquidity factor portfolio return, and HCMLC is the financial contagion factor portfolio return. The stock and factor sample in Panel B covers the period from January 1968 to December 2011.

Panel A: Bank Stock Summary Statistics								
	N	MEAN	SD	MEDIAN	Q25	Q75	MIN	MAX
PRICE	5,783,608	20.453	19.521	16.375	9.725	26.000	0.010	710.750
RET	5,783,608	0.000	0.036	0.000	-0.010	0.010	-2.855	2.485
MVE	5,783,608	1.426	8.910	0.077	0.026	0.302	0.000	286.494
BIR	5,783,608	0.001	0.016	0.001	-0.006	0.007	-0.147	0.176
$\widehat{z}_{t\|t}$	5,783,608	0.097	0.390	0.085	0.026	0.164	-19.289	121.208
$FC_t^{(i)}$	5,783,608	0.032	0.139	0.001	0.000	0.008	-1.400	3.884
FC_t	5,783,608	0.179	0.035	0.178	0.150	0.197	0.089	0.275
Panel B: Full Stock Sample and Factor Summary Statistics								
	N	MEAN	SD	MEDIAN	Q25	Q75	MIN	MAX
PRICE	2,501,921	24.814	767.104	12.813	5.625	24.250	0.016	141,600.000
RET	2,501,921	0.012	0.177	0.000	-0.067	0.072	-0.981	24.000
MVE	2,501,921	1.217	8.481	0.079	0.021	0.370	0.000	602.433
VOL	2,264,164	6.670	62.983	0.403	0.081	2.280	0.000	20,124.269
MRKT	2,501,921	0.005	0.047	0.009	-0.023	0.036	-0.232	0.161
SMB	2,501,921	0.001	0.033	0.000	-0.017	0.021	-0.164	0.220
HML	2,501,921	0.004	0.031	0.004	-0.013	0.019	-0.126	0.138
MOM	2,501,921	0.008	0.045	0.008	-0.007	0.029	-0.347	0.184
LIQ	2,501,921	0.005	0.036	0.003	-0.016	0.025	-0.105	0.212
HCMLC	2,501,921	0.006	0.039	0.005	-0.020	0.032	-0.120	0.166

Table 2.2
Bank Contagion Portfolio Returns

This table presents mean returns from contagion sorted bank portfolios in panel A. Each month, banks are sorted into equal-weighted portfolios based on their contribution to the total financial contagion estimate. In the following month returns on the portfolio are observed and banks are re-sorted. MEAN denotes the time series mean of portfolio returns, T-STAT tests if MEAN is statistically different from zero, and SHARPE presents the Sharpe ratio of the portfolio. D10 is the decile of most contagious banks, D1 is the decile of least contagious banks, Q5 is the quintile of most contagious banks, Q1 is the quintile of least contagious banks, T3 is the tercile of most contagious banks, and T1 is the tercile of least contagious banks. MVE is mean bank market value of equity (in billions) in the portfolio. In panel B, portfolio returns are regressed on the FFCPS 5 factors

$$r^e_{p,t} = \alpha_p + \beta_{p,MRKT} r_{MRKT,t} + \beta_{p,SMB} r_{SMB,t} + \beta_{p,HML} r_{HML,t} + \beta_{p,MOM} r_{MOM,t} + \beta_{p,LIQ} r_{LIQ,t} + \varepsilon_{p,t}$$

ALPHA is the annualized regression intercept, MRKT denotes the excess market return, SMB is the return on the small-minus-big portfolio, HML is the return on the high book value minus low book value portfolio, MOM is the return on the winners minus losers portfolio, and LIQ is the return on high liquidity exposure minus low liquidity exposure portfolio. Stock returns are trimmed at the 2.5% and 97.5% levels. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers from January 1968 to December 2011.

Panel A: Portfolio Returns

	MEAN	T-STAT	SHARPE	MVE
D10	0.119***	4.472	0.372	8.303
D1	0.059***	3.592	0.049	0.273
Q5	0.122***	5.015	0.427	4.490
Q1	0.053***	3.516	-0.002	0.155
T3	0.112***	4.903	0.386	2.788
T1	0.055***	3.717	0.019	0.106
D10-D1	0.060***	2.852	0.430	.
Q5-Q1	0.069***	3.900	0.588	.
T3-T1	0.057***	3.905	0.589	.

Panel B: Portfolio Abnormal Returns

	ALPHA	MRKT	SMB	HML	MOM	LIQ
D10	0.010	0.932***	-0.094**	0.375***	-0.051*	-0.042
	(0.588)	(30.224)	(-2.161)	(7.949)	(-1.698)	(-1.147)
D1	-0.030**	0.401***	0.315***	0.274***	-0.036*	-0.028
	(-2.469)	(17.745)	(9.919)	(7.917)	(-1.646)	(-1.042)
Q5	0.009	0.847***	0.075*	0.410***	-0.020	-0.033
	(0.628)	(30.687)	(1.944)	(9.709)	(-0.747)	(-0.996)
Q1	-0.035***	0.382***	0.324***	0.269***	-0.024	-0.025
	(-3.358)	(19.252)	(11.624)	(8.865)	(-1.228)	(-1.077)
T3	-0.002	0.776***	0.186***	0.417***	-0.009	-0.027
	(-0.136)	(30.858)	(5.279)	(10.856)	(-0.350)	(-0.910)
T1	-0.034***	0.382***	0.311***	0.281***	-0.019	-0.028
	(-3.298)	(19.739)	(11.454)	(9.521)	(-1.028)	(-1.204)
D10-D1	0.039**	0.531***	-0.409***	0.101*	-0.015	-0.014
	(2.189)	(15.708)	(-8.614)	(1.955)	(-0.448)	(-0.349)
Q5-Q1	0.045***	0.466***	-0.248***	0.141***	0.004	-0.007
	(2.944)	(16.335)	(-6.202)	(3.238)	(0.131)	(-0.216)
T3-T1	0.032***	0.394***	-0.125***	0.136***	0.011	0.000
	(2.634)	(17.212)	(-3.871)	(3.881)	(0.483)	(0.017)

Table 2.3
Bank Contagion Risk and Portfolio Returns

This table presents mean returns and alphas of the contagion sorted bank portfolios in Panel A and monotonicity of trend tests in Panel B. Each month, banks are sorted into equal-weighted portfolios based on their contribution to the total financial contagion estimate. In the following month returns on the portfolio are observed and banks are re-sorted. Contagion sorted decile returns are regressed on the FFCPS 5 factors

$$r^e_{p,t} = \alpha_p + \beta_{p,MRKT} r_{MRKT,t} + \beta_{p,SMB} r_{SMB,t} + \beta_{p,HML} r_{HML,t} + \beta_{p,MOM} r_{MOM,t} + \beta_{p,LIQ} r_{LIQ,t} + \varepsilon_{p,t}$$

ALPHA is the annualized regression intercept, MRKT denotes the excess market return, SMB is the return on the small-minus-big portfolio, and HML is the return on the high book value-minus-low book value portfolio, MOM is the return on the winners-minus-losers portfolio, and LIQ is the return on high liquidity exposure-minus-low liquidity exposure portfolio. Decile 10 is the decile of most contagious banks, decile 1 is the decile of least contagious banks. The regression trend test in Panel B regresses decile portfolio returns on a constant and a trend variable ranging from 1 to 10. INT denotes the regression intercept and TREND is the coefficient on the trend variable. Kendall's tau, TAU, is obtained from the methodology described in Kendall (1938). In Panel A, t-statistics are presented in parentheses. In Panel B, t-statistics are presented in parentheses in columns 1 and 2. Kendall's p-values from Kendall (1975) are presented in parentheses in columns 3 and 4. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 1968 to December 2012.

Panel A: Portfolio Returns

	Decile Portfolio										
	1	2	3	4	5	6	7	8	9	10	10-1
Mean Returns											
MEAN	0.059***	0.047***	0.052***	0.075***	0.074***	0.096***	0.084***	0.102***	0.126***	0.119***	0.060***
	(3.592)	(2.793)	(3.157)	(3.978)	(3.803)	(4.642)	(3.865)	(4.376)	(5.242)	(4.472)	(2.852)
FFML Alphas											
ALPHA	-0.030**	-0.042***	-0.037***	-0.017	-0.020	-0.006	-0.019	-0.014	0.009	0.010	0.039**
	(-2.469)	(-3.084)	(-2.848)	(-1.115)	(-1.335)	(-0.369)	(-1.204)	(-0.889)	(0.551)	(0.588)	(2.189)

Panel B: Return Monotonicity

	Regression Trend Test		Kendall's Tau	
	(1)	(2)	(3)	(4)
INT	0.037***	-0.045***		
	(5.483)	(-7.525)		
TREND	0.008***	0.005***		
	(7.757)	(5.33)		
TAU			0.778***	0.733***
			(0.000)	(0.002)

Table 2.4
Factor Correlations

This table presents the correlation matrix of monthly factor portfolio returns. HCMLC is the high contagion-minus-low contagion bank portfolio return, MRKT denotes the excess market return, SMB is the return on the small-minus-big portfolio, and HML is the return on the high book value-minus-low book value portfolio, MOM is the return on the winners-minus-losers portfolio, LIQ is the return on high liquidity exposure-minus-low liquidity exposure portfolio, DEF is the monthly log change in the log difference between yields on Baa and Aaa rated bonds, and VIX is the monthly log return of the Chicago Board Options Exchange Volatility Index. Monthly data is used. The sample period covers January 1968 to December 2011 for correlations excluding the VIX. The sample period for correlations including the VIX is January 1990 to December 2011.

	MRKT	SMB	HML	MOM	LIQ	DEF	VIX	HCMLC
MRKT	1.000							
SMB	0.307	1.000						
HML	-0.321	-0.241	1.000					
MOM	-0.131	-0.026	-0.149	1.000				
LIQ	-0.052	-0.039	0.031	-0.023	1.000			
DEF	0.022	-0.059	-0.003	-0.042	-0.002	1.000		
VIX	-0.652	-0.186	0.143	0.147	-0.043	0.090	1.000	
HCMLC	0.494	-0.152	-0.042	-0.099	-0.029	0.111	-0.344	1.000

Table 2.5
Betas and Expected Returns

This table presents mean returns on deciles sorted on financial contagion beta in Panel A. Deciles are sorted based on financial contagion beta in month t from the following regressions

$$r^e_{i,t} = \beta_{i,0} + \beta_{i,MRKT} r_{MRKT,t} + \beta_{i,HCMLC} r_{HCMLC,t}$$
$$r^e_{i,t} = \beta_{i,0} + \beta_{i,MRKT} r_{MRKT,t} + \beta_{i,SMB} r_{SMB,t} + \beta_{i,HML} r_{HML,t} + \beta_{i,MOM} r_{MOM,t} + \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t}$$

MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion bank portfolio return factor. The regression trend test in panel B regresses decile portfolio returns on a constant and a trend variable ranging from 1 to 10. INT denotes the regression intercept and TREND is the coefficient on the trend variable. Kendall's tau, TAU, is obtained from the methodology described in Kendall (1938). Stock returns are trimmed at the 2.5% and 97.5% levels. t-statistics are presented in parentheses in Panel A. In Panel B, t-statistics are presented in parentheses in columns 1 and 2. Kendall's p-values from Kendall (1975) are presented in columns 3 and 4. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers January 1968 to December 2011.

Panel A: Beta Sorted Portfolio Mean Returns

	Decile										
	1	2	3	4	5	6	7	8	9	10	10-1
Univariate:											
	0.033	0.051	0.064*	0.043	0.041	0.053**	0.077***	0.072***	0.086***	0.071**	0.039
	(0.808)	(1.366)	(1.815)	(1.254)	(1.432)	(2.045)	(3.087)	(2.92)	(3.323)	(2.452)	(1.214)
Multivariate:											
	0.053	0.035	0.03	0.05**	0.052**	0.072***	0.068***	0.075***	0.072**	0.069**	0.016
	(1.494)	(1.094)	(1.092)	(1.972)	(2.061)	(2.883)	(2.676)	(2.83)	(2.572)	(2.143)	(0.66)

Panel B: Monotonicity in Portfolio Returns

	Regression Trend Test		Kendall's Tau	
	(1)	(2)	(3)	(4)
INT	0.034***	0.034***		
	(4.328)	(4.871)		
TREND	0.004***	0.004***		
	(3.506)	(3.760)		
TAU			0.556**	0.533**
			(0.028)	(0.037)

Table 2.6
Financial Contagion Risk Premium

This table presents the results of second-stage Fama and MacBeth (1973) regressions. A 60-month window is used for the first-stage beta estimations. Fama-MacBeth second-stage regressions are estimated without the intercept term

$$
\begin{aligned}
r^e_{i,t} = \ & \beta_{i,0} + \beta_{i,MRKT} r_{MRKT,t} + \beta_{i,SMB} r_{SMB,t} + \beta_{i,MOM} r_{MOM,t} \\
& + \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t} \\
r^e_{t+1} = \ & \lambda_{MRKT} \widehat{\beta}_{MRKT,t} + \lambda_{SMB} \widehat{\beta}_{SMB,t} + \lambda_{HML} \widehat{\beta}_{HML,t} \\
& + \lambda_{MOM} \widehat{\beta}_{MOM,t} + \lambda_{LIQ} \widehat{\beta}_{LIQ,t} + \lambda_{HCMLC} \widehat{\beta}_{HCMLC,t} + u_t \\
\overline{\lambda}_k = \ & \frac{1}{T} \sum_{t=1}^{T} \widehat{\lambda}_{k,t} \\
\sigma^2\left(\overline{\lambda}_k\right) = \ & \widehat{h}(0) + 2 \sum_{j=1}^{\lfloor 0.25T \rfloor} w_j h(j) \\
w_j = \ & 1 - \frac{j}{\left(\lfloor T^{\frac{1}{4}} \rfloor + 1\right)} \\
\widehat{h}(j) = \ & \frac{1}{T} \sum_{t=1}^{T-j} \left(\widehat{\lambda}_{k,t+j} - \overline{\lambda}_k\right)\left(\widehat{\lambda}_{k,t} - \overline{\lambda}_k\right)
\end{aligned}
$$

Annualized risk premium coefficients, $\overline{\lambda}_k$, are presented. t-statistics from Newey and West (1987) autocorrelation consistent standard errors, $\sqrt{\sigma^2\left(\overline{\lambda}_k\right)}$, are presented in parentheses. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion return factor. Returns are trimmed at the 2.5% and 97.5% levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers 1968 to December 2011.

	HCMLC	CAPM	FF3F	FFCPS
MRKT		0.057**	0.047**	0.047**
		(2.007)	(1.941)	(1.943)
SMB			0.007	0.007
			(0.456)	(0.446)
HML			0.027**	0.027**
			(2.487)	(2.517)
MOM				0.011
				(1.036)
LIQ				-0.024**
				(-1.591)
HCMLC	0.096***	0.054***	0.040***	0.039***
	(2.625)	(3.971)	(3.378)	(3.348)

Table 2.7
Pricing Test Portfolios

This table presents the results of second-stage Fama and MacBeth (1973) regressions. The estimation procedure is the same as presented in Table 2.6. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity factor, and HCMLC is the high contagion-minus-low contagion return factor. EQ WEIGHT indicates that the portfolio is equally-weighted and VA WEIGHT indicates that the portfolio is value-weighted. Portfolio returns are trimmed at the 2.5% and 97.5% levels in the first-stage factor regressions. t-statistics from Newey and West (1987) autocorrelation consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers January 1968 to December 2011.

	MRKT	SMB	HML	MOM	LIQ	HCMLC
49 Industry:						
EQ WEIGHT	0.069**	0.025	0.048**	-0.012	-0.066**	0.100***
	(1.992)	(0.769)	(1.969)	(-0.406)	(-1.942)	(2.655)
VA WEIGHT	0.090***	0.034*	0.027	-0.006	-0.017	0.047*
	(3.022)	(1.500)	(1.490)	(-0.240)	(-0.596)	(1.841)
10 Size:						
EQ WEIGHT	-0.036	-0.004	-0.036	-0.064	-0.066	0.135**
	(-0.663)	(-0.091)	(-0.854)	(-1.051)	(-0.894)	(2.009)
VA WEIGHT	-0.030	0.036	-0.048	-0.003	-0.117	0.156**
	(-0.504)	(0.760)	(-1.023)	(-0.034)	(-1.196)	(1.732)
10 B/M:						
EQ WEIGHT	0.111	0.102*	0.011	-0.105	0.108	0.005
	(1.286)	(1.772)	(0.201)	(-0.853)	(0.876)	(0.059)
VA WEIGHT	0.074	0.025	0.026	0.001	-0.043	0.149**
	(1.859)	(0.412)	(0.699)	(0.008)	(-0.445)	(2.035)
10 Momentum:						
EQ WEIGHT	0.207***	0.124*	-0.007	-0.241**	0.201*	0.234**
	(2.779)	(1.875)	(-0.092)	(-3.000)	(2.298)	(2.201)
VA WEIGHT	0.089**	0.061	0.010	-0.105	0.054	0.076
	(1.762)	(1.821)	(0.199)	(-1.721)	(1.035)	(1.271)
25 Size-B/M+10 Momentum:						
EQ WEIGHT	0.118***	0.076***	0.039*	-0.006	0.049	0.058*
	(2.920)	(2.633)	(1.678)	(-0.121)	(1.440)	(2.053)
VA WEIGHT	0.111***	0.057***	0.044**	0.059*	0.052*	0.034
	(2.949)	(2.054)	(1.862)	(1.734)	(1.520)	(1.042)

Table 2.8
Ex-ante Pricing Error Tests

This table presents Chi-square tests testing if all pricing errors are jointly equal to zero. Fama-MacBeth (1973) regressions are used. A 60-month window is used for the first-stage beta estimations and second-stage regressions are estimated without the intercept term

$$
\begin{aligned}
r^e_{i,t} =\ & \beta_{i,0} + \beta_{i,MRKT} r_{MRKT,t} + \beta_{i,SMB} r_{SMB,t} + \beta_{i,HML} r_{HML,t} + \beta_{i,MOM} r_{MOM,t} \\
& + \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t} \\
r^e_{t+1} =\ & \lambda_{MRKT} \widehat{\beta}_{MRKT,t} + \lambda_{SMB} \widehat{\beta}_{SMB,t} + \lambda_{HML} \widehat{\beta}_{HML,t} + \lambda_{MOM} \widehat{\beta}_{MOM,t} \\
& + \lambda_{LIQ} \widehat{\beta}_{LIQ,t} + \lambda_{HCMLC} \widehat{\beta}_{HCMLC,t} + \alpha_t \\
\widehat{\boldsymbol{\alpha}} =\ & T^{-1} \sum_{t=1}^{T} \widehat{\boldsymbol{\alpha}}_t \\
cov\left(\widehat{\boldsymbol{\alpha}}\right) =\ & T^{-2} \sum_{t=1}^{T} \left(\widehat{\boldsymbol{\alpha}}_t - \widehat{\boldsymbol{\alpha}}\right)\left(\widehat{\boldsymbol{\alpha}}_t - \widehat{\boldsymbol{\alpha}}\right)' \\
\widehat{\boldsymbol{\alpha}}' cov\left(\widehat{\boldsymbol{\alpha}}\right) \widehat{\boldsymbol{\alpha}} \sim\ & \chi^2_{N-k}
\end{aligned}
$$

χ^2_{N-k} estimates are presented. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion return factor. Returns are trimmed at the 2.5% and 97.5% levels. ***, **, and * denote statistical significance at the 1%, 5%, 10% levels, respectively. The sample period covers January 1968 to December 2011.

	CAPM	FF3F	FFCPS	HCMLC
49 Industry	72.871***	76.421***	70.001***	70.803**
10 Size	11.900	5.666	10.796*	15.724*
10 B/M	37.488***	31.617***	20.624***	26.655***
10 Momentum	35.751***	18.024**	14.104**	29.615***
25 Size-B/M+10 Momentum	130.849***	112.885***	108.616***	101.926***

Table 2.9
Price of Risk in Cross Section

This table presents asset pricing test results of the price of financial contagion risk in the cross-section of test portfolio returns. The following two-pass cross-section methodology is used

$$r^e_{i,t} = \beta_{i,0} + \beta_{i,MRKT} r_{MRKT,t} + \beta_{i,SMB} r_{SMB,t} + \beta_{i,HML} r_{HML,t} + \beta_{i,MOM} r_{MOM,t} + \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t}$$
$$\overline{r}^e_i = \lambda_{MRKT}\widehat{\beta}_{i,MRKT} + \lambda_{SMB}\widehat{\beta}_{i,SMB} + \lambda_{HML}\widehat{\beta}_{i,HML} + \lambda_{MOM}\widehat{\beta}_{i,MOM} + \lambda_{LIQ}\widehat{\beta}_{i,LIQ} + \lambda_{HCMLC}\widehat{\beta}_{i,HCMLC} + u_i$$

$\overline{r}^e_i$ is the sample mean excess return of portfolio i and hats denote estimated values. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion bank portfolio return factor. OLS denotes that estimates were obtained from OLS, GLS_1 denotes that estimates were obtained using FGLS using the error variance matrix from eqn. (2.17a)-(2.17e), and GLS_2 denotes that estimates were obtained from FGLS using the error variance matrix from eqn. (2.18a,b). Shanken (1992) standard errors are presented in parentheses. SF denotes the Shanken adjustment factor. Returns are trimmed at the 2.5% and 97.5% levels in the first-stage factor regression. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers January 1968 to December 2011.

		MRKT	SMB	HML	MOM	LIQ	HCMLC	N	FFCP $\overline{R}^2$	$\overline{R}^2$	SF
49 Industry:	OLS	0.089***	-0.019	-0.020	0.133***	-0.044**	0.066***	49	-0.009	-0.027	1.122
		(3.633)	(-1.165)	(-1.255)	(5.689)	(-2.374)	(3.136)				
	GLS_1	0.083***	-0.018	-0.036**	0.139***	-0.078***	0.072***	49	-0.068	-0.098	1.146
		(3.381)	(-1.063)	(-2.313)	(5.992)	(-4.202)	(3.408)				
	GLS_2	0.083***	-0.008	-0.035	0.079	-0.070	0.056*	49	-0.097	-0.122	1.081
		(3.329)	(-0.316)	(-1.510)	(1.312)	(-1.209)	(1.723)				
10 Size:	OLS	0.060**	0.028*	-0.021	-0.112***	-0.231***	0.128***	10	0.794	0.898	1.423
		(2.460)	(1.698)	(-1.306)	(-4.739)	(-12.196)	(6.061)				
	GLS_1	0.055**	0.025	0.012	-0.129***	-0.246***	0.155***	10	0.665	0.889	1.509
		(2.268)	(1.481)	(0.772)	(-5.465)	(-12.979)	(7.323)				
	GLS_2	0.069**	0.032	0.001	-0.144	-0.178	0.079	10	0.628	0.748	1.276
		(2.530)	(1.221)	(0.006)	(-1.060)	(-1.239)	(0.997)				
10 B/M:	OLS	0.070***	0.045***	0.056***	0.151***	-0.383***	0.101***	10	0.525	0.416	2.016
		(2.870)	(2.674)	(3.531)	(6.121)	(-18.315)	(4.564)				
	GLS_1	0.039	0.004	0.072***	0.158***	-0.473***	0.219***	10	0.486	0.304	2.639
		(1.575)	(0.261)	(4.573)	(6.159)	(-20.832)	(9.478)				
	GLS_2	0.078	0.095	0.055**	0.070	-0.332	0.087	10	0.486	0.370	1.790
		(1.335)	(0.896)	(2.087)	(0.321)	(-1.449)	(0.483)				
10 Momentum:	OLS	-0.003	-0.144***	-0.115***	0.452***	0.103***	0.57***	10	0.737	0.812	3.893
		(-0.137)	(-8.528)	(-6.484)	(18.308)	(5.533)	(25.500)				
	GLS_1	-0.011	-0.125***	-0.101***	0.551***	0.103***	0.597***	10	0.730	0.797	4.450
		(-0.445)	(-7.216)	(-4.812)	(18.865)	(5.471)	(23.424)				
	GLS_2	0.016	-0.068	-0.136	0.493**	0.083	0.460**	10	0.637	0.761	3.342
		(0.257)	(-0.788)	(-0.746)	(2.128)	(1.569)	(2.014)				
25 Size-B/M+10 Momentum:	OLS	0.063***	0.105***	0.076***	0.503***	0.080***	0.135***	35	0.659	0.686	2.456
		(2.586)	(6.264)	(4.824)	(21.252)	(4.298)	(6.357)				
	GLS_1	0.074***	0.103***	0.064***	0.406***	0.017	0.111***	35	0.570	0.612	1.972
		(3.012)	(6.159)	(4.060)	(17.318)	(0.890)	(5.248)				
	GLS_2	0.074***	0.087***	0.074***	0.212***	0.117***	0.102**	35	0.591	0.602	1.527
		(2.839)	(4.872)	(4.373)	(3.588)	(4.302)	(2.129)				

Table 2.10
Ex-post Pricing Error Tests

This table presents Chi-square tests testing if all pricing errors are jointly equal to zero. Two-pass cross sectional regressions are used

$$
\begin{aligned}
r^e_{i,t} =&\ \beta_{i,0} + \beta_{i,MRKT} r_{MRKT,t} + \beta_{i,SMB} r_{MRKT,t} + \beta_{i,HML} r_{HML,t} + \beta_{i,MOM} r_{MOM,t} \\
&+ \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t} \\
\overline{r}^e_i =&\ \lambda_{MRKT}\widehat{\beta}_{i,MRKT} + \lambda_{SMB}\widehat{\beta}_{i,SMB} + \lambda_{HML}\widehat{\beta}_{i,HML} + \lambda_{MOM}\widehat{\beta}_{i,MOM} \\
&+ \lambda_{LIQ}\widehat{\beta}_{i,LIQ} + \lambda_{HCMLC}\widehat{\beta}_{i,HCMLC} + \alpha_i \\
\widehat{\boldsymbol{\alpha}} =&\ \overline{\boldsymbol{r}}^e - \widehat{\boldsymbol{\beta}}\widehat{\boldsymbol{\lambda}} \\
\boldsymbol{\Sigma}^{(i,j)} =&\ \frac{\boldsymbol{\varepsilon}'_i \boldsymbol{\varepsilon}_j}{T-k} \\
\boldsymbol{\Sigma}_f^{(i,j)} =&\ \frac{1}{T}\left(\boldsymbol{f}_i - \overline{f}_i\right)'\left(\boldsymbol{f}_j - \overline{f}_j\right) \\
cov\left(\widehat{\boldsymbol{\alpha}}\right) =&\ \frac{1}{T}\left(\boldsymbol{I}_N - \widehat{\boldsymbol{\beta}}\left(\widehat{\boldsymbol{\beta}}'\widehat{\boldsymbol{\beta}}\right)^{-1}\widehat{\boldsymbol{\beta}}\right)\boldsymbol{\Sigma}\left(\boldsymbol{I}_N - \widehat{\boldsymbol{\beta}}\left(\widehat{\boldsymbol{\beta}}'\widehat{\boldsymbol{\beta}}\right)^{-1}\widehat{\boldsymbol{\beta}}\right)' \times \left(1 + \widehat{\boldsymbol{\lambda}}'\boldsymbol{\Sigma}_f\widehat{\boldsymbol{\lambda}}\right) \\
\widehat{\boldsymbol{\alpha}}' cov\left(\widehat{\boldsymbol{\alpha}}\right)\widehat{\boldsymbol{\alpha}} \sim&\ \chi^2_{N-k}
\end{aligned}
$$

χ^2_{N-k} estimates are presented. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion return factor. Returns are trimmed at the 2.5% and 97.5% levels. ***, **, and * denote statistical significance at the 1%, 5%, 10% levels, respectively. The sample period covers January 1968 to December 2011.

	CAPM	FF3F	FFCPS	HCMLC
49 Industry	64.225*	67.360**	58.329*	70.201**
10 Size	12.422	4.436	2.683	13.641
10 B/M	26.436***	13.387*	7.122	24.443***
10 Momentum	45.246***	14.311**	9.448*	39.987***
25 Size-B/M+10 Momentum	111.898***	92.320***	60.723	114.150***

Table 2.11
Beta Estimation Robustness

This table presents the results of second-stage Fama and MacBeth (1973) regressions for the firm-level stock sample. The estimation procedure is the same as in Table 2.6, except monthly beta estimation windows in the first-stage regression are varied. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion return factor. Stock returns are trimmed at the 2.5% and 97.5% levels. t-statistics from Newey and West (1987) autocorrelation consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers January 1968 to December 2011.

	MRKT	SMB	HML	MOM	LIQ	HCMLC
48 mos	0.041*	0.004	0.027***	0.015**	-0.018	0.035***
	(1.707)	(0.286)	(2.621)	(1.368)	(-1.134)	(3.342)
60 mos	0.047**	0.007	0.027**	0.011	-0.024**	0.039***
	(1.943)	(0.446)	(2.517)	(1.036)	(-1.591)	(3.348)
72 mos	0.056**	0.010	0.027**	0.004	-0.024**	0.041***
	(2.284)	(0.648)	(2.253)	(0.287)	(-1.619)	(3.160)
84 mos	0.066***	0.009	0.025**	0.002	-0.026**	0.048***
	(2.864)	(0.597)	(1.845)	(0.139)	(-1.662)	(3.683)
96 mos	0.062***	0.007	0.028**	0.003	-0.024*	0.044***
	(2.720)	(0.409)	(2.191)	(0.188)	(-1.53)	(3.197)
108 mos	0.064***	0.005	0.022*	0.006	-0.022*	0.047***
	(2.700)	(0.276)	(1.666)	(0.333)	(-1.29)	(3.171)
120 mos	0.068***	0.005	0.022*	0.008	-0.015	0.048***
	(2.722)	(0.285)	(1.538)	(0.440)	(-0.819)	(3.027)

Table 2.12
Beta Estimation Robustness: Test Portfolios

This table presents the results of second-stage Fama and MacBeth (1973) regressions for test portfolios. The estimation procedure is the same as in Table 2.6, except monthly beta estimation windows in the first-stage regression are varied. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion return factor. Test portfolios are value-weighted. Test portfolio returns are trimmed at the 2.5% and 97.5% levels. t-statistics from Newey and West (1987) autocorrelation consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers January 1968 to December 2011.

	48 mos	60 mos	72 mos	84 mos	96 mos	108 mos	120 mos
49 Industry	0.075***	0.047*	0.042*	0.055**	0.056**	0.057**	0.054*
	(2.891)	(1.841)	(1.634)	(2.176)	(1.890)	(1.797)	(1.647)
10 Size	0.093	0.156**	0.026	-0.014	0.006	-0.054	-0.048
	(1.091)	(1.732)	(0.362)	(-0.198)	(0.092)	(-0.838)	(-0.645)
10 B/M	0.135**	0.149**	0.192***	0.176***	0.084	0.067	0.125
	(2.011)	(2.035)	(2.677)	(2.857)	(1.290)	(0.991)	(1.751)
10 Momentum	0.008	0.076	0.134*	0.133	0.055	0.166*	0.384***
	(0.092)	(1.271)	(1.958)	(1.503)	(0.603)	(1.920)	(4.322)
25 Size-B/M+10 Momentum	0.059**	0.034	0.048	0.053*	0.028	0.041	0.047
	(2.051)	(1.042)	(1.488)	(1.736)	(0.731)	(1.094)	(1.242)

Table 2.13
Subsample Robustness

This table presents the results of second-stage Fama and MacBeth (1973) regressions using the common stock sample. The estimation procedure is the same as presented in Table 2.6. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion return factor. TREND and TAU are defined as in Tables 2.3 and 2.5. Stock returns are trimmed at the 2.5% and 97.5% levels. t-statistics from Newey and West (1987) autocorrelation consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	MRKT	SMB	HML	MOM	LIQ	HCMLC	TREND	TAU
1975-1980	0.143**	0.104**	-0.001	-0.007	-0.066*	0.034***	0.007	0.378
	(2.600)	(2.103)	(-0.054)	(-0.266)	(-1.514)	(4.025)	(1.605)	(0.156)
1980-1985	0.034	0.056*	0.044*	0.017	-0.041	0.050	0.007***	0.556**
	(0.456)	(1.166)	(2.403)	(0.689)	(-0.805)	(1.186)	(3.679)	(0.028)
1985-1990	0.064	0.000	0.014	-0.006	0.043**	0.064*	0.004	0.244
	(1.004)	(0.017)	(0.699)	(-0.600)	(1.550)	(1.677)	(1.526)	(0.380)
1990-1995	0.040	0.003	-0.003	-0.025	-0.022	0.055*	0.000	0.067
	(0.515)	(0.076)	(-0.097)	(-0.902)	(-1.005)	(1.695)	(0.077)	(0.862)
1995-2000	0.086*	0.001	0.000	-0.019	0.014	0.083***	0.009***	0.733***
	(1.729)	(0.043)	(-0.008)	(-0.661)	(1.041)	(2.776)	(5.065)	(0.002)
2000-2005	0.029	-0.010	0.100*	0.046*	-0.129***	0.010	0.009*	0.422
	(0.437)	(-0.155)	(2.669)	(1.316)	(-2.444)	(0.329)	(1.687)	(0.108)
2005-2010	0.012	-0.036	0.021	0.055**	-0.004	0.021	-0.004	-0.089
	(0.131)	(-1.007)	(1.279)	(1.959)	(-0.118)	(0.840)	(-1.160)	(0.762)

Table 3.1
ETF Summary Statistics

This table presents summary statistics for ETF fund characteristics. N is the number of ETFs, INCEPTION is the mean ETF inception date, SIZE is mean ETF market-cap (in billions of dollars), VOL is mean ETF daily trading volume (in shares), FEES is mean ETF expense ratio (in percentage points), CUNIT is mean creation unit size (in shares), and CUCOST is the mean per-share cost (in percentage points) of creating/redeeming a creation unit. The sample period is March 1996 to December 2011.

CLASS	N	INCEPTION	SIZE	VOL	FEES (%)	CUNIT	CUCOST(%)
All	224	05M2002	1.445	1,263,790	0.400	91,825	0.064
U.S. Equities	60	03M2002	0.999	1,272,320	0.394	52,595	0.024
U.S. Fixed income	29	01M2006	2.092	451,240	0.208	91,656	0.004
Foreign equities	77	05M2000	1.547	1,989,103	0.523	154,359	0.136
Foreign fixed income	6	12M2008	0.485	62,383	0.449	101,715	0.010
Miscellaneous	26	08M2007	0.982	137,181	0.376	58,967	0.051

Table 3.2
Premium Adjustment Statistics

This table presents statistics of the regression coefficient statistics that are used to adjust premiums of ETFs investing in foreign equities and foreign fixed income to make them synchronous with market prices. Premiums are adjusted by the following equations

$$ln\left(P_{i,t}\right) - ln\left(NAV_{i,t}\right) = \alpha_i \triangle ln\left(NAV_{i,t}\right) + \phi_i r_{MRKT,t} + u_{i,t}$$
$$\widehat{NAV}^{*}_{i,t} = exp\left[ln\left(P_{i,t}\right) - \widehat{u}_{i,t}\right]$$

where $P_{i,t}$ is the nominal ETF market price, $NAV_{i,t}$ is the nominal net asset value, $r_{MRKT,t}$ is the daily return on the U.S. market portfolio, and $\triangle$ denotes the difference operator. $\widehat{u}_{i,t} \times 100$ is the estimated synchronous premium. Panel A presents estimated regression coefficients. N denotes the number of observations, MEAN is the mean, SD is the standard deviation, MED is the median, Q25 (Q75) is the twenty-fifth percentile (seventy-fifth percentile), MIN (MAX) is the minimum (maximum) value. Panel B presents the variance of recorded premiums divided by the variance of adjusted premiums (VR). The F-test is used to test if the ratio of variances is significantly different from one. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is March 1996 to December 2011.

Panel A: Regression Coefficient Estimates

	N	MEAN	SD	MED	Q25	Q75	MIN	MAX
ALPHA	83	-0.104***	0.018	-0.091	-0.145	-0.050	-0.980	0.226
PHI	83	0.004***	0.000	0.004	0.003	0.006	0.000	0.011

Panel B: Variance Ratios

TICKER	N	VR	TICKER	N	VR	TICKER	N	VR
AAXJ	850	2.214***	EIRL	414	1.096	EWS	3,983	1.341***
ACWI	948	2.120***	EIS	948	1.612***	EWT	2,899	1.698***
ACWV	48	2.886***	EMB	1,015	1.045	EWU	3,987	1.423***
ACWX	948	3.195***	EMFN	489	1.311***	EWW	3,982	1.071
AIA	1,037	2.916***	EMIF	638	1.867***	EWY	2,919	2.174***
AOR	789	1.011	EMMT	489	1.095	EWZ	2,886	1.065
AXDI	368	1.576***	ENZL	334	2.454***	EWZS	316	1.035
AXEN	368	1.052	EPHE	316	2.402***	EZA	2,240	2.132***
AXFN	489	1.204**	EPOL	403	1.881***	EZU	2,874	1.864***
AXHE	368	1.196**	EPP	2,563	2.924***	FCHI	886	2.632***
AXID	368	1.615***	EPU	637	1.026	FEFN	489	1.899***
AXIT	368	1.145	ERUS	286	1.722***	FXI	1,820	3.240***
AXMT	368	1.259***	ESR	565	1.807***	GTIP	154	1.026
AXSL	368	1.183**	EUFN	489	1.699***	IDV	1,143	2.008***
AXTE	368	1.374***	EWA	3,981	1.699***	IEV	2,873	1.444***
AXUT	368	1.141	EWC	3,984	1.041***	IFSM	1,037	1.548***
BKF	1,037	2.088***	EWD	3,983	1.469***	IGOV	740	1.009
ECH	1,037	1.074	EWG	3,986	1.480***	ILF	2,562	1.016
ECNS	316	2.409***	EWH	3,977	1.900***	IOO	2,780	1.493***
EEM	2,196	2.632***	EWI	3,983	1.394***	ISHG	740	1.006
EEMS	92	2.215***	EWJ	3,977	2.113***	ITIP	154	1.068
EEMV	48	2.451***	EWK	3,978	1.216***	LEMB	48	0.961
EFA	2,607	2.878***	EWL	3,981	1.262***	MCHI	189	2.112***
EFAV	48	1.494	EWM	3,976	1.024	SCJ	1,013	2.048***
EFG	1,613	3.414***	EWN	3,981	1.425***	SCZ	1,020	1.736***
EFV	1,613	3.396***	EWO	3,980	1.186***	THD	948	2.385***
EIDO	416	1.767***	EWP	3,983	1.412***	TOK	1,018	1.000
			EWQ	3,984	1.508***	TUR	948	2.068***

Table 3.3
ETF Premium and Tracking Errors

This table presents ETF premium statistics in Panel A and tracking error statistics in Panel B. Premiums and tracking errors for fund i at time t are defined as

$$PREM_{i,t} = \begin{cases} ln\left(P_{i,t}/NAV_{i,t}\right) \times 100 & \textit{for domestic ETFs} \\ \widehat{u}_{i,t} \times 100 & \textit{for foreign ETFs} \end{cases}$$
$$TE_{i,t} = \left(r_{i,t}^{NAV} - r_{i,t}^{INDEX}\right) \times 100$$

$P_{i,t}$ denotes nominal ETF share price, $NAV_{i,t}$ denotes nominal ETF net asset value, $\widehat{u}_{i,t}$ is the estimated true premium obtained from eqns. (3.2a,b), $r_{i,t}^{NAV}$ is NAV return, and $r_{i,t}^{INDEX}$ is the return on the underlying index that the ETF aims to replicate. N is the number of daily observations, MEAN is the mean, SD is the standard deviation, MED is the median, Q25 (Q75) is the twenty-fifth (seventy-fifth) percentile, MIN is the minimum value, and MAX is the maximum value. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is March 1996 to December 2011.

Panel A: Premium Statistics								
CLASS	N	MEAN	SD	MED	Q25	Q75	MIN	MAX
All	370,974	0.116***	0.818	0.041	-0.097	0.279	-35.978	32.896
U.S. Equities	134,954	0.026***	0.423	0.000	-0.085	0.111	-16.790	18.112
U.S. Fixed income	32,995	0.371***	0.783	0.168	0.029	0.508	-11.621	12.011
Foreign equities	128,638	0.159***	1.158	0.144	-0.285	0.578	-35.978	32.896
Foreign fixed income	2,857	0.684***	0.948	0.600	0.199	1.083	-9.156	12.590
Miscellaneous	24,150	0.162***	0.921	0.093	-0.088	0.345	-14.021	17.848
Panel B: Tracking Error Statistics								
CLASS	N	MEAN	SD	MED	Q25	Q75	MIN	MAX
All	370,974	0.000	0.228	-0.001	-0.013	0.011	-21.056	33.165
U.S. Equities	134,954	0.000	0.177	-0.001	-0.009	0.007	-11.675	13.153
U.S. Fixed income	32,995	-0.001***	0.070	0.000	-0.008	0.006	-4.091	3.744
Foreign equities	128,638	0.000	0.333	-0.002	-0.039	0.036	-21.056	33.165
Foreign fixed income	2,857	-0.001	0.140	-0.002	-0.018	0.012	-2.931	5.753
Miscellaneous	24,150	0.000	0.116	0.000	-0.017	0.016	-3.401	4.475

Table 3.4
ETF Premium Determinants

This table presents regression results of the effect that market segmentation has on ETF premiums. The panel regression model is

$$\overline{PREM}_{i,t} = \beta_0 + \beta_1 TESD_{i,t-1} + \beta_2 \overline{BAS}_{i,t-1} + \beta_3 \overline{PI}_{i,t-1} + \beta_4 \overline{FEES}_{i,t-1} + \boldsymbol{\phi}' \overline{\mathbf{x}}_{i,t-1} + \varepsilon_{i,t}$$

where $PREM$ is the ETF premium, $TESD$ is the within-month standard deviation of daily tracking errors, BAS the percentage bid-ask spread of the ETF, PI is the Amihud (2002) illiquidity measure for the ETF, and FEES is ETF expense ratio (in percentage points). $\overline{\mathbf{x}}$ is a vector of control variables including daily dividend yield (DIV, in percentage points), daily risk-free rate (RF, in percentage points), daily ETF squared returns (VAR), daily ETF trading volume (VOL, in millions of shares), daily market value of equity ($SIZE$, in billions of dollars), ETF age (AGE, in years), and lagged within-month mean ETF premium ($LPREM$). Bars above variables denote within-month means. Time fixed-effects are included in columns four and five. ETF fixed-effects are included in column five. t-statistics from White (1980) heteroskedasticity-consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 1% levels, respectively. The sample period is March 1996 to December 2011.

	(1)	(2)	(3)	(4)	(5)
INT	0.019**	0.008**	0.060***		
	(2.135)	(2.564)	(4.027)		
TESD	0.089**	0.117*	0.095*	0.135**	0.135**
	(2.046)	(1.935)	(1.804)	(2.424)	(2.181)
BAS	0.026		0.026	0.022	0.024
	(1.255)		(1.204)	(1.065)	(1.046)
PI	-0.012		-0.016	-0.017	-0.012
	(-0.753)		(-1.095)	(-1.185)	(-0.936)
FEES			-0.003	0.002	0.153
			(-0.088)	(0.052)	(0.721)
DIV			-0.075	0.138	-1.851
			(-0.377)	(0.653)	(-0.489)
RF			-1.428***	-12.524***	-0.004*
			(-2.956)	(-5.098)	(-1.798)
VAR			-0.001	-0.005***	0.001
			(-1.016)	(-2.597)	(1.144)
VOL			0.000	-0.001	-0.002**
			(-1.326)	(-1.562)	(-2.379)
SIZE			0.001*	0.001*	0.020**
			(1.684)	(1.690)	(2.479)
AGE			-0.005***	-0.005***	
			(-3.846)	(-4.210)	
FOR		0.030***			
		(4.001)			
FI		0.123***			
		(4.978)			
LPREM	0.651***	0.648***	0.646***	0.652***	0.611***
	(10.716)	(10.547)	(10.516)	(11.57)	(9.839)
TIME F.E.	No	No	No	Yes	Yes
ETF F.E.	No	No	No	No	Yes
N	17,721	17,721	17,721	17,721	17,721
$\overline{R}^2$	0.440	0.441	0.441	0.488	0.496

Table 3.5
ETF Premium Error Correction

This table presents Engle and Granger (1987) error correction speeds for ETF premiums. Speed of error correction in premiums is estimated from the following regression

$$P_{i,t} = c_{i,0} + c_{i,1} NAV_{i,t} + \varepsilon_{i,t}$$
$$\triangle P_{i,t} = a_{i,1} + a_{i,2}\widehat{\varepsilon}_{i,t-1} + \sum_{j=1}^{k} a_{i,11}\left(j\right)\triangle P_{i,t-j} + \sum_{j=1}^{k} a_{i,12}\left(j\right)\triangle NAV_{i,t-j} + e_{i,t}$$

where $P_{i,t}$ is the nominal ETF share price, $NAV_{i,t}$ is the nominal ETF net asset value, and $PREM_{i,t}$ is ETF premium. k is equal to five. $\widehat{a}_{i,2}$ statistics are reported. N is the number of ETFs, MEAN is the mean, SD is the standard deviation, MED is the median, Q25 (Q75) is the twenty-fifth (seventy-fifth) percentile, MIN is the minimum value, and MAX is the maximum value. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is March 1996 to December 2011.

CLASS	N	MEAN	SD	MED	Q25	Q75	MIN	MAX
All	223	-0.437***	0.499	-0.278	-0.734	-0.082	-2.458	0.397
U.S. Equities	60	-0.701***	0.565	-1.023	-0.681	-0.278	-2.457	0.247
U.S. Fixed income	29	-0.075***	0.107	-0.085	-0.062	-0.046	-0.411	0.247
Foreign equities	77	-0.181***	0.259	-0.315	-0.164	-0.063	-0.867	0.397
Foreign fixed income	5	-0.155	0.237	-0.215	-0.081	0.028	-0.538	0.032
Miscellaneous	26	-0.487***	0.380	-0.717	-0.430	-0.151	-1.442	0.029

Table 3.6
Premium Error Correction Speed Determinants

This table presents results of tests of ETF premium error-correction (EC) speed determinants. The estimated cross-sectional regression is

$$\widehat{a}_{i,2} = \beta_0 + \beta_1 TESD_i + \beta_2 \overline{BAS}_i + \beta_3 \overline{PI}_i + \boldsymbol{\phi}'\overline{\mathbf{x}}_i + v_i$$

where $\widehat{a}_{i,2}$ is estimated using eqn. (3.7). $TESD$ is the sample standard deviation of tracking errors, BAS is the percentage bid-ask spread, PI is Amihud (2002) illiquidity. $\overline{\mathbf{x}}_i$ is a vector of control variables including daily dividend yield (DIV, in percentage points), daily risk-free rate (RF, in percentage points), squared ETF returns (VAR), daily trading volume (VOL, in millions of shares), market value of equity ($SIZE$, in billions of dollars), ETF age (AGE, in years), expense ratio ($FEES$, in percentage points), creation unit size ($CUNIT$, in shares), and per share fee of creating/redeeming a creation unit ($CUCOST$). Bars above variables denote sample means. Full sample results are presented in columns one and two. Regression results using subsets of the ETF type indicated in the header are presented in columns three to six. t-statistics from White (1980) heteroskedasticity-consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is March 1996 to December 2011.

	Full Sample		Domestic	Foreign	Equities	Fixed Income
	(1)	(2)	(3)	(4)	(5)	(6)
INT	-0.499***	-0.639***	-0.053	0.111	-0.675***	-0.190
	(-9.405)	(-5.982)	(-0.191)	(0.523)	(-4.319)	(-1.164)
TESD	0.390**	0.442**	0.782	0.247*	0.448**	0.900*
	(2.427)	(2.193)	(0.983)	(1.673)	(2.213)	(1.845)
BAS	0.014	0.020	-0.016	-0.169**	0.054	0.140
	(0.325)	(0.427)	(-0.055)	(-2.291)	(0.761)	(0.728)
PI	0.010	-0.026	1.142	-0.115	-0.187	-1.855
	(0.156)	(-0.441)	(0.367)	(-1.168)	(-1.263)	(-0.424)
DIV		1.625	2.473	-6.875*	10.885**	-10.777***
		(0.316)	(0.215)	(-1.807)	(2.500)	(-2.628)
RF		7.745	-23.689	54.432*	-87.006**	-6.088
		(0.234)	(-0.476)	(1.829)	(-2.128)	(-0.177)
VAR		-0.026	-0.043	0.020	-0.009	0.029
		(-1.105)	(-1.192)	(1.188)	(-0.372)	(0.137)
VOL		-0.021***	-0.029*	-0.025***	0.008	-0.797***
		(-3.134)	(-1.752)	(-4.196)	(0.891)	(-2.644)
SIZE		-0.001	0.027	0.013*	-0.023	0.088**
		(-0.086)	(0.484)	(1.665)	(-1.555)	(2.151)
AGE		-0.028	-0.039	-0.082	0.096	-0.015
		(-0.484)	(-0.405)	(-1.629)	(1.442)	(-0.184)
FEES		0.413	-0.503	-0.256	0.190	-0.072
		(1.416)	(-0.740)	(-0.716)	(0.560)	(-0.296)
CUNIT		0.109**	-0.008	0.038	0.120**	0.305*
		(2.255)	(-0.037)	(1.156)	(2.446)	(1.929)
CUCOST		0.000	0.000	0.000**	0.000	0.000*
		(0.359)	(1.011)	(-2.291)	(0.517)	(-1.655)
Time F.E.	No	No	No	No	No	No
ETF F.E.	No	No	No	No	No	No
N	217	217	84	82	136	30
$\overline{R}^2$	0.003	0.034	0.014	0.131	0.177	0.170

Table 3.7
Domestic and Foreign ETF Premiums

This table presents subsample regression results when domestic and foreign ETF subsamples. The panel regression model is

$$\overline{PREM}_{i,t} = \beta_0 + \beta_1 TESD_{i,t-1} + \beta_2 \overline{BAS}_{i,t-1} + \beta_3 \overline{PI}_{i,t-1} + \beta_4 \overline{FEES}_{i,t-1} + \boldsymbol{\phi}' \overline{\mathbf{x}}_{i,t-1} + \varepsilon_{i,t}$$

where $PREM$ is ETF premium, $TESD$ is the within-month standard deviation of daily NAV tracking errors, BAS the percentage bid-ask spread of the ETF, PI is the Amihud (2002) illiquidity measure for the ETF, and $FEES$ is ETF expense ratio. $\overline{\mathbf{x}}$ is a vector of control variables including daily dividend yield (DIV, in percentage points), daily risk-free rate (RF, in percentage points), daily ETF squared returns (VAR), daily ETF trading volume (VOL, in millions of shares), daily market value of equity ($SIZE$, in billions of dollars), ETF age (AGE, in years), and lagged within-month mean ETF premium ($LPREM$). Bars above variables denote within-month means. Time fixed-effects are included in columns two, three, five, and six. ETF fixed-effects are included in columns three and six. t-statistics from White (1980) heteroskedasticity consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is March 1996 to December 2011.

	Domestic			Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)
INT	0.076***			0.135**		
	(5.116)			(2.228)		
TESD	0.065	0.070*	0.045	0.096	0.166**	0.193**
	(1.581)	(1.709)	(1.139)	(1.260)	(2.142)	(2.100)
BAS	0.089**	0.097**	0.123**	0.023	0.019	0.024
	(2.261)	(2.195)	(2.562)	(0.585)	(0.407)	(0.478)
PI	-0.502**	-0.445**	-0.416**	-0.018	-0.015	-0.009
	(-2.329)	(-2.128)	(-2.100)	(-1.624)	(-1.201)	(-0.879)
FEES	-0.090**	-0.039		-0.128	-0.170	
	(-2.510)	(-1.032)		(-1.591)	(-1.602)	
DIV	-0.341**	-0.181	-0.100	-0.021	0.027	-0.092
	(-2.074)	(-0.965)	(-0.536)	(-0.076)	(0.083)	(-0.272)
RF	-2.092***	-7.389***	6.150*	-0.719	-27.774***	-7.099
	(-5.872)	(-3.678)	(1.840)	(-0.399)	(-2.906)	(-0.675)
VAR	-0.002**	-0.007***	-0.007***	0.000	-0.001	0.002
	(-2.050)	(-4.201)	(-3.870)	(-0.125)	(-0.110)	(0.216)
VOL	0.000	0.000	0.002***	-0.001	-0.001	-0.001
	(-0.693)	(-0.149)	(3.042)	(-0.589)	(-1.572)	(-0.798)
SIZE	0.002	0.003	-0.008**	0.000	0.001	0.000
	(1.094)	(1.434)	(-2.551)	(0.157)	(0.882)	(-0.086)
AGE	-0.005***	-0.009***	0.024***	-0.006**	-0.004**	0.044***
	(-2.842)	(-4.809)	(3.636)	(-2.144)	(-2.056)	(2.878)
LPREM	0.716***	0.696***	0.580***	0.631***	0.644***	0.625***
	(22.168)	(21.680)	(16.366)	(8.238)	(8.868)	(8.273)
TIME F.E.	No	Yes	Yes	No	Yes	Yes
ETF F.E.	No	No	Yes	No	No	Yes
N	8,019	8,019	8,019	6,276	6,276	6,276
$\overline{R}^2$	0.578	0.595	0.621	0.412	0.474	0.477

Table 3.8
Fixed Income and Equities ETF Premiums

This table presents regression results when fixed income and equities ETFs are partitioned into subsamples. The panel regression model is

$$\overline{PREM}_{i,t} = \beta_0 + \beta_1 TESD_{i,t-1} + \beta_2 \overline{BAS}_{i,t-1} + \beta_3 \overline{PI}_{i,t-1} + \beta_4 \overline{FEES}_{i,t-1} + \boldsymbol{\phi}'\overline{\mathbf{x}}_{i,t-1} + \varepsilon_{i,t}$$

where $PREM$ is ETF premium, $TESD$ is the within-month standard deviation of daily NAV tracking errors, BAS the percentage bid-ask spread of the ETF, PI is the Amihud (2002) illiquidity measure for the ETF, and $FEES$ is ETF expense ratio. $\overline{\mathbf{x}}$ is a vector of control variables including daily dividend yield (DIV, in percentage points), daily risk-free rate (RF, in percentage points), daily ETF squared returns (VAR), daily ETF trading volume (VOL, in millions of shares), daily market value of equity ($SIZE$, in billions of dollars), ETF age (AGE, in years), and lagged within-month mean ETF premium ($LPREM$). Bars above variables denote within-month means. Time fixed-effects are included in columns two, three, five, and six. ETF fixed-effects are included in columns three and six. t-statistics from White (1980) heteroskedasticity consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is March 1996 to December 2011.

	Fixed Income			Equities		
	(1)	(2)	(3)	(4)	(5)	(6)
INT	-0.003			0.000		
	(-0.075)			(0.006)		
TESD	0.743***	0.489*	0.454	0.078	0.118**	0.126**
	(2.806)	(1.652)	(1.567)	(1.527)	(2.192)	(2.013)
BAS	0.210	0.130	0.142	0.029	0.025	0.027
	(1.512)	(0.961)	(1.087)	(0.862)	(0.655)	(0.633)
PI	-0.659	1.175	0.600	-0.018	-0.017	-0.016
	(-0.349)	(0.654)	(0.251)	(-1.265)	(-1.114)	(-1.257)
FEES	0.341**	0.561***		0.065	0.021	
	(1.979)	(3.117)		(1.237)	(0.366)	
DIV	-1.968	-7.447	-7.753*	-0.012	0.160	0.099
	(-0.83)	(-1.493)	(-1.947)	(-0.057)	(0.703)	(0.431)
RF	0.497	2.777	27.895***	-0.467	-14.187***	-2.494
	(0.32)	(0.680)	(3.560)	(-0.598)	(-3.708)	(-0.412)
VAR	0.032	0.006	-0.005	0.000	0.001	0.002
	(0.801)	(0.142)	(-0.149)	(-0.191)	(0.540)	(0.789)
VOL	-0.008	-0.004	0.004	0.000	-0.001	0.000
	(-1.030)	(-0.451)	(0.568)	(-0.961)	(-1.502)	(0.749)
SIZE	0.006	0.004	-0.017**	0.001	0.001	-0.002
	(1.313)	(1.008)	(-2.454)	(0.927)	(1.391)	(-1.584)
AGE	-0.010	-0.006	0.101***	-0.003*	-0.002*	0.023**
	(-1.576)	(-0.759)	(3.869)	(-1.904)	(-1.718)	(2.111)
LPREM	0.661***	0.636***	0.525***	0.627***	0.635***	0.617***
	(17.010)	(14.892)	(11.255)	(8.343)	(9.097)	(8.515)
TIME F.E.	No	Yes	Yes	No	Yes	Yes
ETF F.E.	No	No	Yes	No	No	Yes
N	1,715	1,715	1,715	12,585	12,585	12,585
$\overline{R}^2$	0.578	0.606	0.633	0.413	0.468	0.469

Table 3.9
Investor Sentiment Robustness

This table presents regression results from regressing ETF premiums on tracking error standard deviation, an investor sentiment measure, and controls. The panel regression model is

$$\overline{PREM}_{i,t} = \beta_0 + \beta_1 TESD_{i,t-1} + \beta_2 \overline{SENT}^{(k)}_{i,t-1} + \beta_3 \overline{FEES}_{i,t-1} + \boldsymbol{\phi}' \overline{\mathbf{x}}_{i,t-1} + \varepsilon_{i,t}$$

where $k \in \{MRKT, SMB, FLOW\}$, $PREM$ is the ETF premium, $TESD$ is the within-month standard deviation of daily NAV tracking errors. $\overline{\mathbf{x}}$ is a vector of control variables including the percentage bid-ask spread of the ETF (BAS), the Amihud (2002) illiquidity measure for the ETF (PI), daily dividend yield (DIV, in percentage points), daily risk-free rate (RF, in percentage points), daily ETF squared returns (VAR), daily ETF trading volume (VOL, in millions of shares), daily market value of equity ($SIZE$, in billions of dollars), ETF age (AGE, in years), and lagged within-month mean ETF premium ($LPREM$). $MRKT$ returns are used as the sentiment variable in columns one to two, SMB returns are used as the sentiment variable in columns three to four, and $FLOW$ is used as the sentiment variable in columns five to six. Bars above variables denote within-month means. Time fixed-effects are included in columns two, three, five, and six. ETF fixed-effects are included in columns there and six. t-statistics from White (1980) heteroskedasticity-consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is March 1996 to December 2011.

	MRKT		SMB		FLOW	
	(2)	(3)	(4)	(5)	(6)	(7)
TESD	0.135**	0.135**	0.135**	0.136**	0.135**	0.135**
	(2.425)	(2.182)	(2.427)	(2.194)	(2.425)	(2.182)
SENT	0.023	0.028	-0.348***	-0.306***	0.004	0.007
	(0.257)	(0.329)	(-3.244)	(-3.041)	(0.156)	(0.243)
BAS	0.022	0.024	0.022	0.024	0.022	0.024
	(1.063)	(1.045)	(1.067)	(1.043)	(1.065)	(1.046)
PI	-0.017	-0.012	-0.017	-0.012	-0.017	-0.012
	(-1.191)	(-0.940)	(-1.184)	(-0.947)	(-1.185)	(-0.936)
FEES	0.002		0.003		0.002	
	(0.050)		(0.088)		(0.052)	
DIV	0.137	0.152	0.142	0.154	0.139	0.153
	(0.649)	(0.717)	(0.668)	(0.727)	(0.654)	(0.722)
RF	-12.387***	-1.811	-13.299***	-3.285	-12.523***	-1.851
	(-4.999)	(-0.481)	(-5.442)	(-0.879)	(-5.099)	(-0.489)
VAR	-0.005**	-0.004*	-0.005***	-0.004*	-0.005***	-0.004*
	(-2.575)	(-1.774)	(-2.613)	(-1.815)	(-2.596)	(-1.798)
VOL	-0.001	0.001	-0.001	0.001	-0.001	0.001
	(-1.565)	(1.139)	(-1.572)	(1.118)	(-1.562)	(1.142)
SIZE	0.001*	-0.002**	0.001*	-0.002**	0.001*	-0.002**
	(1.691)	(-2.371)	(1.689)	(-2.394)	(1.69)	(-2.378)
AGE	-0.005***	0.020**	-0.005***	0.018**	-0.005***	0.020**
	(-4.211)	(2.391)	(-4.222)	(2.259)	(-4.214)	(2.480)
LPREM	0.652***	0.611***	0.652***	0.611***	0.652***	0.611***
	(11.571)	(9.839)	(11.574)	(9.843)	(11.566)	(9.835)
TIME F.E.	Yes	Yes	Yes	Yes	Yes	Yes
ETF F.E.	No	Yes	No	Yes	No	Yes
N	17,721	17,721	17,721	17,721	17,721	17,721
$\overline{R}^2$	0.488	0.496	0.488	0.496	0.488	0.496

Table 3.10
ETF Premiums and Returns

This table presents premium coefficients from regression results with holding period returns as the dependent variable. Remaining coefficient estimates are omitted to conserve space. The pooled regression model is

$$\begin{aligned} RET_{i,t+h}^{(k)} &= \beta_0 + \beta_1 \overline{PREM}_{i,t} + \beta_2 \overline{SIZE}_{i,t} + \beta_3 \overline{FLOW}_{i,t} + \beta_4 \overline{VAR}_{i,t} + \beta_5 \overline{AGE}_{i,t} \\ &\quad + \beta_6 \overline{FEES}_{i,t} + \beta_7 RET_{i,t}^{(k)} + \varepsilon_{i,t} \\ FLOW_{i,t} &= \left(AUM_{i,t} - AUM_{i,t-1} \left[1 + RET_{i,t}^{(NAV)} \right] \right) / AUM_{i,t-1} \end{aligned}$$

where $k \in \{NAV, MRKT, SMB\}$, $h \in \{1, 3, 6, 12\}$ denotes the holding period return, $PREM$ is ETF premium, $SIZE$ is ETF market cap (in billions of dollars), VAR is daily ETF squared return, AGE is ETF age (in years), and $FEES$ is ETF expense ratio (in percentage points). Bars above variables denote within-month means. t-statistics from White (1980) heteroskedasticity-consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is March 1996 to December 2011.

	Holding Period (h months)			
	1	3	6	12
NAV	0.021	-0.091**	-0.085	0.032
	(0.662)	(-2.184)	(-1.445)	(0.442)
SMB	0.012	-0.044**	-0.03	0.073
	(0.84)	(-2.317)	(-1.259)	(1.081)
MRKT	-0.044	-0.156***	-0.064*	-0.091
	(-1.617)	(-4.148)	(-1.759)	(-1.641)

Table 3.11
Determinants of Tracking Error Standard Deviation

This table presents regression results from regressing tracking error variability on replication risk determinants. The panel regression model is

$$TESD_{i,t} = \beta_0 + \beta_1 ZEROS_{i,t} + \beta_2 \overline{FEES}_{i,t} + \beta_3 \overline{INDVAR}_{i,t} + \boldsymbol{\phi}'\overline{\mathbf{x}}_{i,t} + \varepsilon_{i,t}$$

$TESD$ is the within-month standard deviation of tracking errors. Tracking errors are defined as the difference between ETF NAV return and the return on the index that the ETF aims to replicate. $ZEROS$ is the number of within-month zero returns, $FEES$ is the ETF expense ratio (in percentage points), and $INDVAR$ is the underlying index squared daily return. $\overline{\mathbf{x}}$ is a vector of control variables including daily ETF dividend yield (DIV, in percentage points), the daily risk-free rate (RF, in percentage points), ETF market value of equity ($SIZE$, in billions of dollars), ETF age (AGE, in years), and lagged $TESD$ ($LTESD$). Bars above variables denote within-month means. Time fixed-effects are included in columns three and four. ETF fixed-effects are included in column four. t-statistics from White (1980) heteroskedasticity-consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is March 1996 to December 2011.

	(1)	(2)	(3)	(4)
INT	0.030***	-0.062***		
	(14.932)	(-12.603)		
ZEROS	0.034***	0.029***	0.027***	0.049***
	(8.384)	(8.196)	(7.497)	(9.191)
FEES		0.246***	0.233***	
		(17.076)	(14.641)	
INDVAR		0.006***	0.004**	0.006***
		(4.558)	(2.245)	(2.628)
DIV		1.300***	1.436***	1.423***
		(7.996)	(6.848)	(6.925)
RF		1.433***	6.100***	6.582
		(5.776)	(2.656)	(1.454)
SIZE		0.003***	0.004***	0.001
		(8.466)	(9.274)	(0.831)
AGE		-0.005***	-0.004***	-0.005
		(-14.156)	(-11.140)	(-0.618)
FOR	0.061***			
	(15.158)			
FI	-0.047***			
	(-11.224)			
LTESD	0.409***	0.358***	0.357***	0.205***
	(12.759)	(12.086)	(11.633)	(7.527)
TIME F.E.	No	No	Yes	Yes
ETF F.E.	No	No	No	Yes
N	17,721	17,721	17,721	17,721
$\overline{R}^2$	0.236	0.312	0.350	0.430

Table 3.12
Determinants of Tracking Error Standard Deviation: Subsample Analysis

This table presents regression results from regressing tracking error variability on replication risk determinants. The panel regression model is

$$TESD_{i,t} = \beta_0 + \beta_1 ZEROS_t + \beta_2 \overline{FEES}_{i,t} + \beta_3 \overline{INDVAR}_{i,t} + \boldsymbol{\phi}'\overline{\mathbf{x}}_{i,t} + \varepsilon_{i,t}$$

$TESD$ is the within-month standard deviation of tracking errors. Tracking errors are defined as the difference between ETF NAV return and the return on the index that the ETF aims to replicate. $ZEROS$ is the number of within-month zero returns, $FEES$ is the ETF expense ratio, and $INDVAR$ is the underlying index squared daily return. $\overline{\mathbf{x}}$ is a vector of control variables including daily ETF dividend yield (DIV, in percentage points), the daily risk-free rate (RF, in percentage points), ETF market value of equity ($SIZE$, in billions of dollars), ETF age (AGE, in years), and lagged within-month standard deviation of tracking errors ($LTESD$). Bars above variables denote within-month standard deviations. Time fixed-effects are included in columns three and four. t-statistics from White (1980) heteroskedasticity-consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is March 1996 to December 2011.

	Domestic (1)	Foreign (2)	Equities (3)	Fixed Income (4)
ZEROS	0.014***	0.055***	0.106***	0.000
	(5.644)	(4.165)	(7.918)	(0.309)
FEES	0.125***	0.358***	0.258***	0.055***
	(7.372)	(5.963)	(11.550)	(2.644)
INDVAR	0.000	0.019***	0.005**	0.075***
	(-0.580)	(2.640)	(2.018)	(3.097)
DIV	1.930***	1.559***	1.452***	0.057
	(11.932)	(5.033)	(6.300)	(0.127)
RF	4.862**	-0.562	5.334*	-2.444**
	(2.538)	(-0.105)	(1.751)	(-2.057)
SIZE	0.002***	0.003***	0.004***	0.004**
	(3.271)	(6.429)	(7.609)	(2.286)
AGE	-0.002***	-0.008***	-0.005***	-0.005**
	(-3.530)	(-8.415)	(-10.225)	(-2.233)
LTESD	0.164***	0.395***	0.352***	0.176**
	(5.467)	(9.330)	(10.824)	(2.395)
TIME F.E.	Yes	Yes		Yes
ETF F.E.	No	No		No
N	8,019	6,276	12,585	1,715
$\overline{R}^2$	0.232	0.426	0.359	0.372

Table 4.1
Sample Fund Categories and Types

This table presents the sample closed-end fund categories on the left hand side of the table and a snapshot of the closed-end fund market in the latest sample year on the right hand side. FREQ (%) indicates the number (percentage) of monthly observations in the sample that fall within a specified category or type. FUNDS lists the number of closed-end funds in each category and MVE is the mean market value of equity (in millions of dollars). The full sample is August 1984 to December 2011.

			Year 2011	
CATEGORY	FREQ	%	FUNDS	MVE
DOMESTIC	40,316	61.7	192	370
EQUITY		15.5	29	731
FIXED INCOME		84.5	163	293
FOREIGN	13,776	21.1	50	336
EQUITY		79.1	39	295
FIXED INCOME		20.9	11	496
MISCELLANEOUS	11,199	17.2	17	140

Table 4.2
Benchmark Returns

This table presents portfolio performance from the naïve trading strategy that buys the portfolio of CEFs that are trading at the lowest premiums and sells the portfolio of CEFs that are trading at the highest premiums. Portfolios are rebalanced monthly. Q5 denotes the quintile of CEFs with the lowest premiums, Q1 denotes the quintile of CEFs with the highest premiums, and MRKT denotes market returns. MEAN is average return, SHARPE is Sharpe ratio, PTO is portfolio turnover, STO is CEF share turnover, and DVOL is dollar trading volume in millions, each of which is annualized. MVE is CEF market-cap in millions of dollars. MRP is the mean Dickey-Fuller mean-reversion parameter for CEFs in a portfolio. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: Full Sample							
PORTFOLIO	MEAN	SHARPE	PTO	MVE	STO	DVOL	MRP
Q5	0.148***	0.735	2.126	371.855	0.593	190.802	-0.119
	(3.339)						
Q1	-0.001	-0.180	2.543	393.081	0.682	256.609	-0.098
	(-0.013)						
Q5-Q1	0.149***	1.519	2.335	382.468	0.638	223.706	-0.108
	(5.667)						
Q5-MRKT	0.093***	0.854	.	.	.	.	.
	(3.185)						
MRKT	0.055	0.170	.	.	.	.	.
	(1.199)						
FULL SAMPLE	.	.	.	284.831	0.596	162.238	-0.117
Panel B: Domestic Sample							
PORTFOLIO	MEAN	SHARPE	PTO	MVE	STO	DVOL	MRP
Q5	0.126***	0.780	2.193	528.959	0.444	188.605	-0.120
	(3.679)						
Q1	0.005	-0.178	2.610	536.779	0.457	251.999	-0.103
	(0.162)						
Q5-Q1	0.121***	1.506	2.402	532.869	0.450	220.302	-0.111
	(5.619)						
Q5-MRKT	0.071**	0.538	.	.	.	.	.
	(2.008)						
MRKT	0.055	0.170	.	.	.	.	.
	(1.199)						
FULL SAMPLE	.	.	.	284.831	0.596	162.238	-0.124
Panel C: Foreign Sample							
PORTFOLIO	MEAN	SHARPE	PTO	MVE	STO	DVOL	MRP
Q5	0.175***	0.625	3.047	308.809	0.739	249.731	-0.101
	(2.744)						
Q1	0.021	-0.017	2.807	201.906	1.098	288.522	-0.076
	(0.254)						
Q5-Q1	0.154***	0.861	2.927	255.357	0.918	269.126	-0.088
	(3.212)						
Q5-MRKT	0.120***	0.827	.	.	.	.	.
	(3.087)						
MRKT	0.055	0.170	.	.	.	.	.
	(1.199)						
FULL SAMPLE	.	.	.	284.831	0.596	162.238	-0.086

Table 4.3
Trading Strategy Returns: Full Sample Results

This table presents portfolio performance from trading strategies using the full sample of CEFs. CEFs are sorted into portfolios of equally-weighted CEFs based on expected returns and portfolios are rebalanced monthly. In Panel A, expected returns are obtained from eqns. (4.3a,b) and in Panel B expected returns are obtained from eqns. (4.4a,b). Q5 (Q1) denotes the quintile of CEFs with the highest (lowest) expected returns and MRKT denotes market returns. MEAN is average return, SHARPE is Sharpe ratio, PTO is portfolio turnover, STO is CEF share turnover, and DVOL is dollar trading volume in millions, each of which is annualized. MVE is CEF market-cap in millions dollars. MRP is the mean Dickey-Fuller mean-reversion parameter for CEFs in a portfolio. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: BMR Model							
PORTFOLIO	MEAN	SHARPE	PTO	MVE	STO	DVOL	MRP
Q5	0.153***	0.785	2.675	311.850	0.626	196.309	-0.148
	(3.543)						
Q1	-0.020	-0.332	3.204	301.989	0.571	164.342	-0.159
	(-0.541)						
Q5-Q1	0.173***	1.862	2.939	306.919	0.598	180.325	-0.154
	(6.946)						
Q5-MRKT	0.098***	0.795	.	.	.	.	.
	(2.967)						
MRKT	0.055	0.170	.	.	.	.	.
	(1.199)						
FULL SAMPLE	.	.	.	284.831	0.596	162.238	-0.133

Panel B: RADF Model							
PORTFOLIO	MEAN	SHARPE	PTO	MVE	STO	DVOL	MRP
Q5	0.163***	0.829	5.686	322.454	0.654	217.767	-0.128
	(3.695)						
Q1	-0.019	-0.321	5.964	309.417	0.572	171.416	-0.137
	(-0.503)						
Q5-Q1	0.182***	1.918	5.825	315.936	0.613	194.591	-0.132
	(7.154)						
Q5-MRKT	0.107***	0.871	.	.	.	.	.
	(3.250)						
MRKT	0.055	0.170	.	.	.	.	.
	(1.199)						
FULL SAMPLE	.	.	.	284.831	0.596	162.238	-0.117

Table 4.4
Monotonicity in Returns

This table presents results from monotonicity tests of closed-end fund optimal trading strategy returns. Q5 (Q1) denotes the quintile of CEFs with the highest (lowest) expected returns. Expected returns are obtained from eqns. (4.4a,b), i.e., the RADF model. Panel A presents annualized realized portfolio mean returns. Panel B reports the trend test result from the following regression:

$$\overline{r}_p = \alpha + \beta x + \varepsilon$$

where $x = (1, 2, 3, 4, 5)'$. TAU is the measure of rank correlation between realized portfolio mean returns and quintile number using the Kendall (1938) methodology. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: Portfolio Returns					
	Q1	Q2	Q3	Q4	Q5
N	24.994	25.263	25.347	25.263	25.665
MEAN	-0.019	0.042	0.086***	0.109***	0.163***
T-STAT	(-0.503)	(1.307)	(2.764)	(3.323)	(3.695)
Panel B: Monotonicity Tests					
α	β		TAU		
-0.053***	0.043***		1.000***		
(-4.821)	(12.957)		(<0.010)		

Table 4.5
Selection Bias Robustness

This table presents mean portfolio returns from trading strategies varying the minimum number of observations that a CEF is required to have prior to entering the sample. The naïve trading strategy buys the quintile portfolio of CEFs that are trading at the lowest premiums and sells the quintile portfolio of CEFs that are trading at the highest premiums. The BMR and RADF strategies buy the quintile with highest expected return and sell the quintile with lowest expected return where expected returns are estimated using eqns. (4.3a,b) for the BMR model and eqns. (4.4a,b) for the RADF model. MINOBS denotes the minimum number of observations that a CEF is required to have prior to entering the sample. All out-of-sample periods end December 2011. The out-of-sample period begins January 1995 when MINOBS is 36 and 60, February 1998 when MINOBS is 120, February 2003 when MINOBS is 180, and February 2008 when MINOBS is 240. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

MINOBS	Naïve	BMR	RADF
36	0.155***	0.142***	0.153***
	(6.158)	(5.578)	(6.807)
60	0.159***	0.139***	0.153***
	(5.940)	(5.428)	(6.468)
120	0.149***	0.158***	0.182***
	(5.667)	(6.946)	(7.154)
180	0.137***	0.144***	0.171***
	(4.508)	(4.356)	(5.269)
240	0.121*	0.158	0.201**
	(1.793)	(1.629)	(2.399)

Table 4.6
Abnormal Returns: Benchmark Strategy

This table presents results from regressing benchmark trading strategy returns on the three Fama and French (1993) factors, the Carhart (1997) winners-minus-losers factor, and the Pástor and Stambaugh (2003) tradable liquidity factor:

$$r^e_{p,t} = \alpha_p + \beta_{p,1} r^e_{MRKT,t} + \beta_{p,2} r_{SMB,t} + \beta_{p,3} r_{HML,t} + \beta_{p,4} r_{WML,t} + \beta_{p,5} r_{LIQ,t} + \varepsilon_{p,t}$$

The benchmark trading strategy buys the quintile portfolio of CEFs trading at the lowest premiums (denoted by Q5) and sells the quintile portfolio of CEFs that are trading at the highest premiums (denoted by Q1). Portfolios are rebalanced monthly. The alphas are annualized. Panel A uses the full sample of CEFs; Panel B uses the subsample of domestic CEFs; and Panel C uses the subsample of foreign CEFs. MRKT is the excess market return, SMB is the small-minus-big portfolio, HML is the high-minus-low book-to-market portfolio, WML is the winners-minus-losers portfolio, and LIQ is the tradable liquidity portfolio. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: Full Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.086***	0.644***	0.147**	-0.128**	-0.125***	0.194***
	(3.335)	(13.560)	(2.422)	(-2.075)	(-3.397)	(3.951)
Q1	-0.062**	0.507***	0.144**	0.136*	-0.117***	0.151***
	(-2.132)	(9.398)	(2.088)	(1.936)	(-2.792)	(2.704)
Q5-Q1	0.148***	0.137***	0.003	-0.264***	-0.008	0.043
	(6.095)	(3.045)	(0.051)	(-4.525)	(-0.236)	(0.929)
Panel B: Domestic Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.071***	0.409***	0.118*	0.060	-0.120***	0.149***
	(2.772)	(8.652)	(1.955)	(0.972)	(-3.261)	(3.045)
Q1	-0.048*	0.302***	0.126**	0.112*	-0.092**	0.127**
	(-1.763)	(6.039)	(1.97)	(1.723)	(-2.379)	(2.444)
Q5-Q1	0.119***	0.107***	-0.008	-0.052	-0.027	0.023
	(5.466)	(2.669)	(-0.152)	(-1.003)	(-0.878)	(0.543)
Panel C: Foreign Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.102***	0.980***	0.203**	-0.141	-0.098*	0.169**
	(2.651)	(13.716)	(2.220)	(-1.511)	(-1.775)	(2.281)
Q1	-0.057	1.016***	0.261*	-0.005	-0.331***	0.260**
	(-0.979)	(9.357)	(1.880)	(-0.038)	(-3.926)	(2.307)
Q5-Q1	0.160***	-0.036	-0.058	-0.135	0.232***	-0.091
	(3.328)	(-0.407)	(-0.513)	(-1.168)	(3.371)	(-0.985)

Table 4.7
Abnormal Returns: RADF Model

This table presents results from regressing RADF trading strategy returns on the FFCPS factors using the full sample of CEFs in Panel A, the subset of domestic CEFs in Panel B, and the subset of foreign CEFs in Panel C. The regression model is

$$r^e_{p,t} = \alpha_p + \beta_{p,1} r^e_{MRKT,t} + \beta_{p,2} r_{SMB,t} + \beta_{p,3} r_{HML,t} + \beta_{p,4} r_{WML,t} + \beta_{p,5} r_{LIQ,t} + \varepsilon_{p,t}$$

The alphas are annualized. CEFs are sorted into quintile portfolios of equally-weighted CEFs based on expected returns obtained from eqns. (4.4a,b) and portfolios are rebalanced monthly. MRKT is the excess market return, SMB is the small-minus-big portfolio, HML is the high-minus-low book-to-market portfolio, WML is the winners-minus-losers portfolio, and LIQ is the tradable liquidity portfolio. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: Full Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.100***	0.590***	0.141**	-0.079	-0.123***	0.204***
	(3.388)	(10.840)	(2.022)	(-1.115)	(-2.909)	(3.619)
Q1	-0.074***	0.431***	0.140**	0.093	-0.161***	0.147***
	(-2.665)	(8.389)	(2.131)	(1.395)	(-4.047)	(2.766)
Q5-Q1	0.174***	0.159***	0.001	-0.172***	0.038	0.057
	(7.198)	(3.565)	(0.014)	(-2.965)	(1.110)	(1.230)
Panel B: Domestic Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.098***	0.295***	0.088	0.082	-0.113***	0.152***
	(3.600)	(5.835)	(1.360)	(1.243)	(-2.883)	(2.913)
Q1	-0.063**	0.279***	0.094	0.049	-0.120***	0.133***
	(-2.389)	(5.709)	(1.509)	(0.775)	(-3.168)	(2.628)
Q5-Q1	0.161***	0.015	-0.007	0.032	0.007	0.019
	(7.826)	(0.401)	(-0.136)	(0.651)	(0.248)	(0.485)
Panel C: Foreign Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.101**	1.071***	0.198*	-0.075	-0.113*	0.253***
	(2.145)	(12.239)	(1.773)	(-0.660)	(-1.663)	(2.788)
Q1	-0.087	0.987***	0.142	0.129	-0.171**	0.141
	(-1.572)	(9.680)	(1.093)	(0.972)	(-2.168)	(1.330)
Q5-Q1	0.188***	0.084	0.056	-0.204*	0.059	0.112
	(4.206)	(1.021)	(0.528)	(-1.897)	(0.912)	(1.310)

Table 4.8
Abnormal Returns: Equities and Fixed Income Samples

This table presents results from regressing RADF trading strategy returns on the FFCPS three factors:

$$r^e_{p,t} = \alpha_p + \beta_{p,1} r^e_{MRKT,t} + \beta_{p,2} r_{SMB,t} + \beta_{p,3} r_{HML,t} + \beta_{p,4} r_{WML,t} + \beta_{p,5} r_{LIQ,t} + \varepsilon_{p,t}$$

The alphas are annualized. CEFs are sorted into quintile portfolios of equally-weighted CEFs based on expected returns obtained from eqns. (4.4a,b) and portfolios are rebalanced monthly. MRKT is the excess market return, SMB is the small-minus-big portfolio, HML is the high-minus-low book-to-market portfolio, WML is the winners-minus-losers portfolio, and LIQ is the tradable liquidity portfolio. Panel A presents results when the subsample of equity CEFs is used. Panel B reports results when the subsample of fixed-income CEFs is used. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: Equities CEF Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.108***	1.128***	0.198**	0.066	-0.108**	0.242***
	(2.859)	(16.106)	(2.222)	(0.724)	(-1.993)	(3.332)
Q1	-0.046	1.010***	0.101	0.180*	-0.119*	0.131
	(-1.089)	(12.834)	(1.011)	(1.766)	(-1.957)	(1.600)
Q5-Q1	0.154***	0.118*	0.097	-0.114	0.011	0.112*
	(4.486)	(1.856)	(1.194)	(-1.383)	(0.226)	(1.687)
Panel B: Fixed Income CEF Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.113***	0.091	0.123*	0.079	-0.113**	0.143**
	(3.645)	(1.595)	(1.679)	(1.066)	(-2.562)	(2.428)
Q1	-0.060*	0.171***	0.141*	0.078	-0.132***	0.131**
	(-1.907)	(2.947)	(1.897)	(1.049)	(-2.958)	(2.202)
Q5-Q1	0.172***	-0.079**	-0.018	0.000	0.019	0.012
	(8.591)	(-2.139)	(-0.371)	(0.007)	(0.667)	(0.308)

Table 4.9
Sample Period Robustness

This table presents portfolio returns from the RADF trading strategy using the first half of the sample (denoted by H1) and the second half of the sample (denoted by H2). The difference between them is denoted by DIF. CEFs are sorted into quintile portfolios of equally-weighted CEFs based on expected returns obtained from eqns. (4.4a,b) and portfolios are rebalanced monthly. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

PORTFOLIO	H1	H2	DIF
Q5	0.163***	0.163***	0.000
	(2.611)	(2.599)	(-0.001)
Q1	-0.025	-0.012	-0.013
	(-0.479)	(-0.230)	(-0.175)
Q5-Q1	0.188***	0.175***	0.013
	(5.559)	(4.596)	(0.255)
Q5-MRKT	0.101**	0.114**	-0.012
	(2.165)	(2.420)	(-0.182)

Table 4.10
Portfolio Returns with Varying Holding Periods

This table presents the alphas from regressing portfolio strategy cumulative returns over the holding period from t to $t+h$ on the FFCPS factors:

$$r^e_{p,t:t+h} = \alpha_p + \beta_{p,1} r^e_{MRKT,t:t+h} + \beta_{p,2} r_{SMB,t:t+h} + \beta_{p,3} r_{HML,t:t+h} + \beta_{p,4} r_{WML,t:t+h} + \beta_{p,5} r_{LIQ,t:t+h} + \varepsilon_{p,t:t+h}$$

The alphas for the various holding periods are not annualized. MRKT is the excess market return, SMB is the small-minus-big portfolio, HML is the high-minus-low book-to-market portfolio, WML is the winners-minus-losers portfolio, and LIQ is the tradable liquidity portfolio. CEFs are sorted into quintile portfolios of equally-weighted CEFs based on expected returns obtained from eqns. (4.4a,b). t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

	Holding Period h (in months)					
Portfolio	1	6	9	12	18	24
Q5	0.008***	0.022***	0.024***	0.042***	0.054***	0.066***
	(3.388)	(3.703)	(3.199)	(4.908)	(4.426)	(4.333)
Q1	-0.006***	0.002	0.012*	-0.002	-0.014	-0.036**
	(-2.665)	(0.372)	(1.719)	(-0.279)	(-1.251)	(-2.420)
Q5-Q1	0.015***	0.020***	0.012	0.044***	0.068***	0.102***
	(7.198)	(3.172)	(1.405)	(4.438)	(4.690)	(5.338)
Q5-MRKT	0.008***	0.022***	0.024***	0.042***	0.054***	0.066***
	(3.388)	(3.703)	(3.199)	(4.908)	(4.426)	(4.333)

Table 4.11
CEF Momentum Strategy

This table presents portfolio performance from trading strategies using the full sample of CEFs. In Panel A, CEFs are sorted into quintile portfolios of equally-weighted CEFs based on mean returns over the entire past history (random walk strategy). In Panel B, CEFs are sorted into quintile portfolios of equally-weighted CEFs based on cumulative returns over the previous h months (momentum strategy), and portfolios are held for h months, where $h = 3$, 6, 9, and 12. MEAN is average return, SHARPE is Sharpe ratio, PTO is portfolio turnover, STO is CEF share turnover, and DVOL is dollar trading volume in millions, each of which is annualized. MVE is CEF market-cap in millions of dollars. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: Portfolio Performance of Random Walk Strategy							
PORTFOLIO	MEAN	SHARPE	PTO	MVE	STO	DVOL	MRP
Q5	0.091	0.292	0.62	462.077	0.81	336.998	-0.096
	-1.525						
Q1	0.087***	0.508	1.621	211.394	0.513	121.734	-0.125
	-2.739						
Q5-Q1	0.005	0.027	1.121	336.735	0.661	229.366	-0.111
	-0.103						
Q5-MRKT	0.036	0.316	.	.	.	.	.
	-1.18						
MRKT	0.055	0.17	.	.	.	.	.
	-1.199						
FULL SAMPLE	.	.	.	284.831	0.596	162.238	-0.11

Panel B: Mean Return of Momentum Strategy				
	Holding Period h (in months)			
PORTFOLIO	3	6	9	12
Q5	0.094***	0.082***	0.073***	0.085***
	-3.274	-4.094	-3.952	-4.807
Q1	0.059*	0.074***	0.099***	0.112***
	-1.866	-2.898	-5.116	-8.018
Q5-Q1	0.035	0.008	-0.026	-0.027*
	-1.227	-0.381	(-1.475)	(-1.646)
Q5-MRKT	0.043**	0.034**	0.021*	0.033***
	-1.993	-2.102	-1.647	-2.958

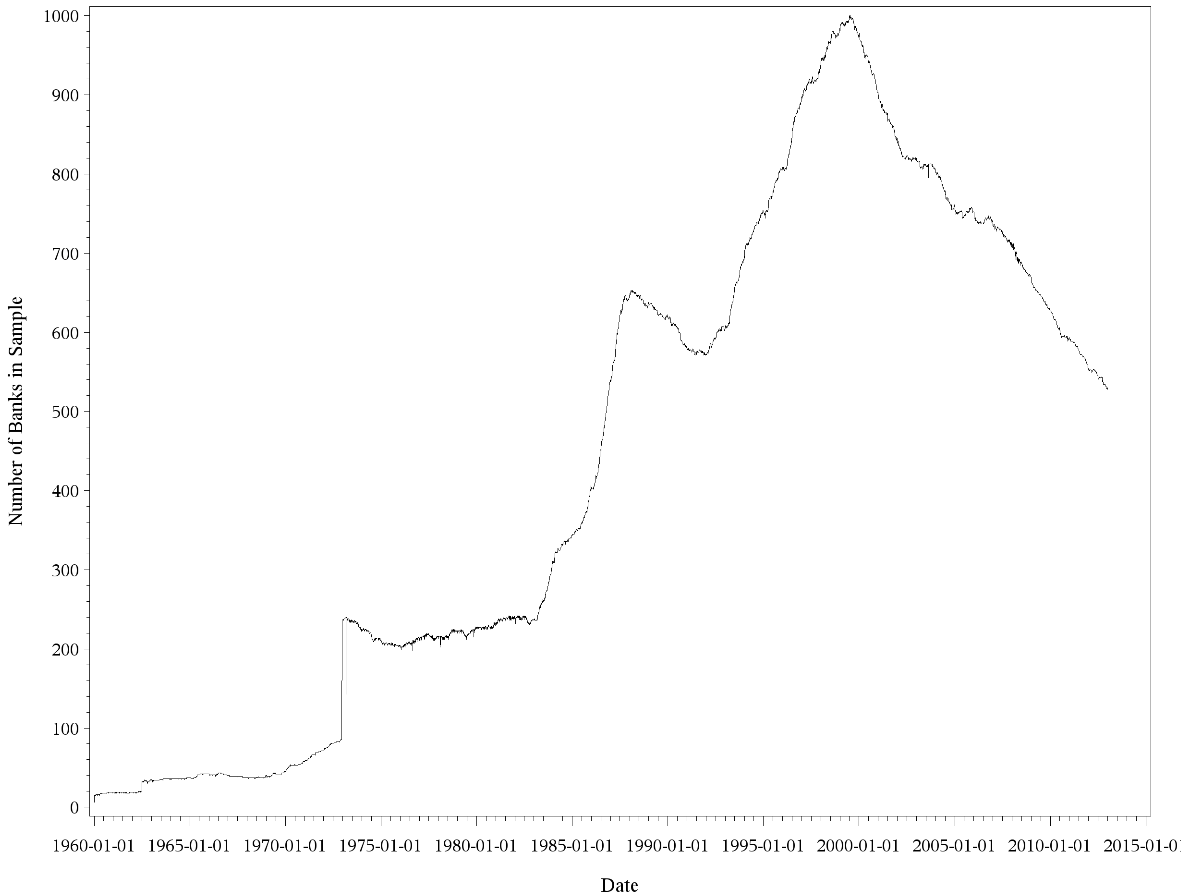


Figure 2.1 Bank Sample Size Time Series. This figure plots the time series of banks (CRSP SIC codes 6000-6299 and share code 10 or 11) contemporaneously present in the sample.

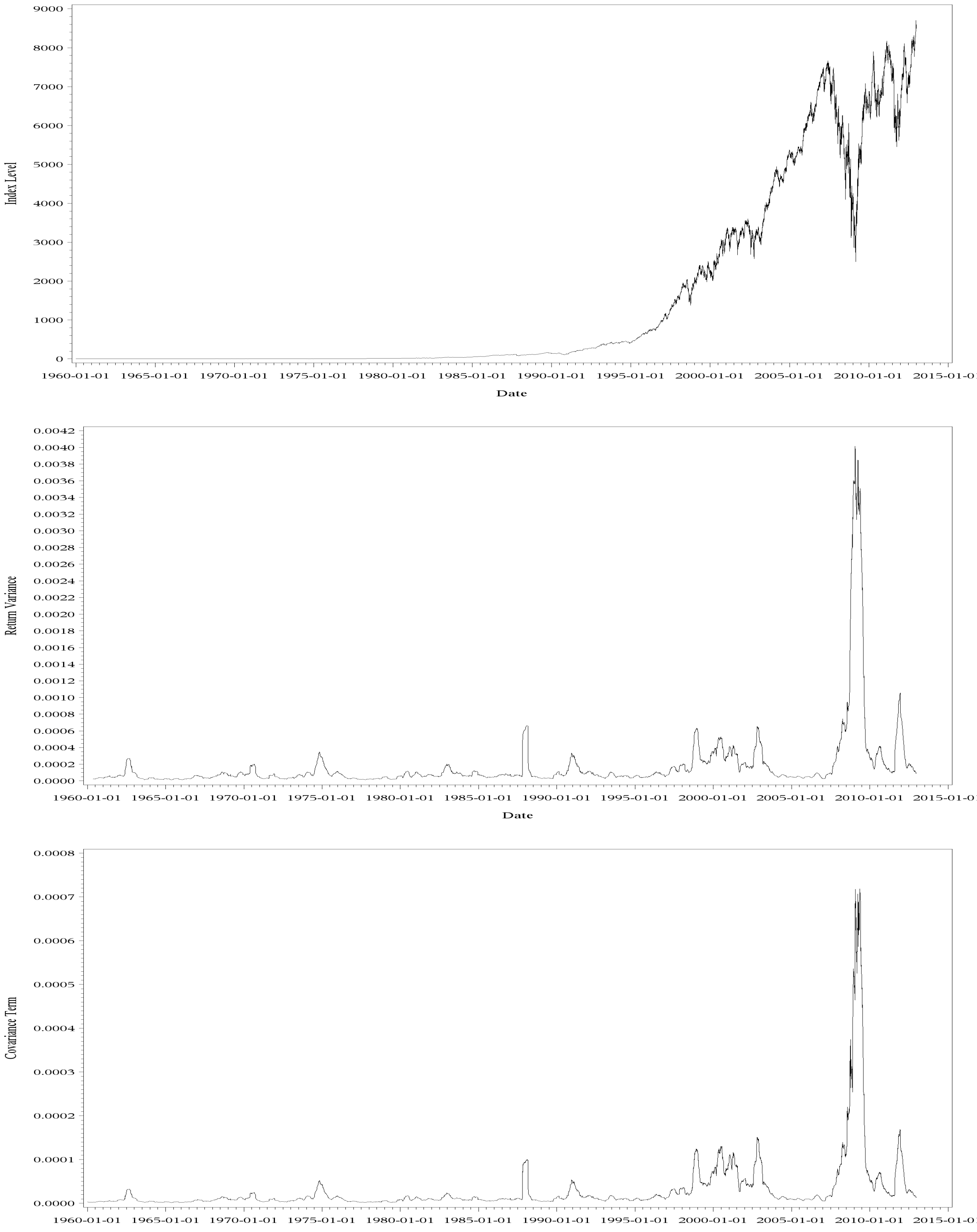


Figure 2.2 Bank Index Time Series. This figure plots the time series of the value-weighted bank index in the top panel, the time series of bank index return variance given by eqn. (2.7b) in the middle panel, and the time series of the covariance term of bank index return variance in the bottom panel. The bank index is constructed as the market-value weighted return of the bank sample. The base level for the bank index is set equal to one on January 1, 1960. Eqns. (2.7a,b) are used to obtain the return variance and covariances are obtained from $FC_t\widehat{\sigma}^2_{r_{I,t}}$. FC_t and $\widehat{\sigma}^2_{r_{I,t}}$ are given by eqns. (2.8) and (2.7b), respectively.

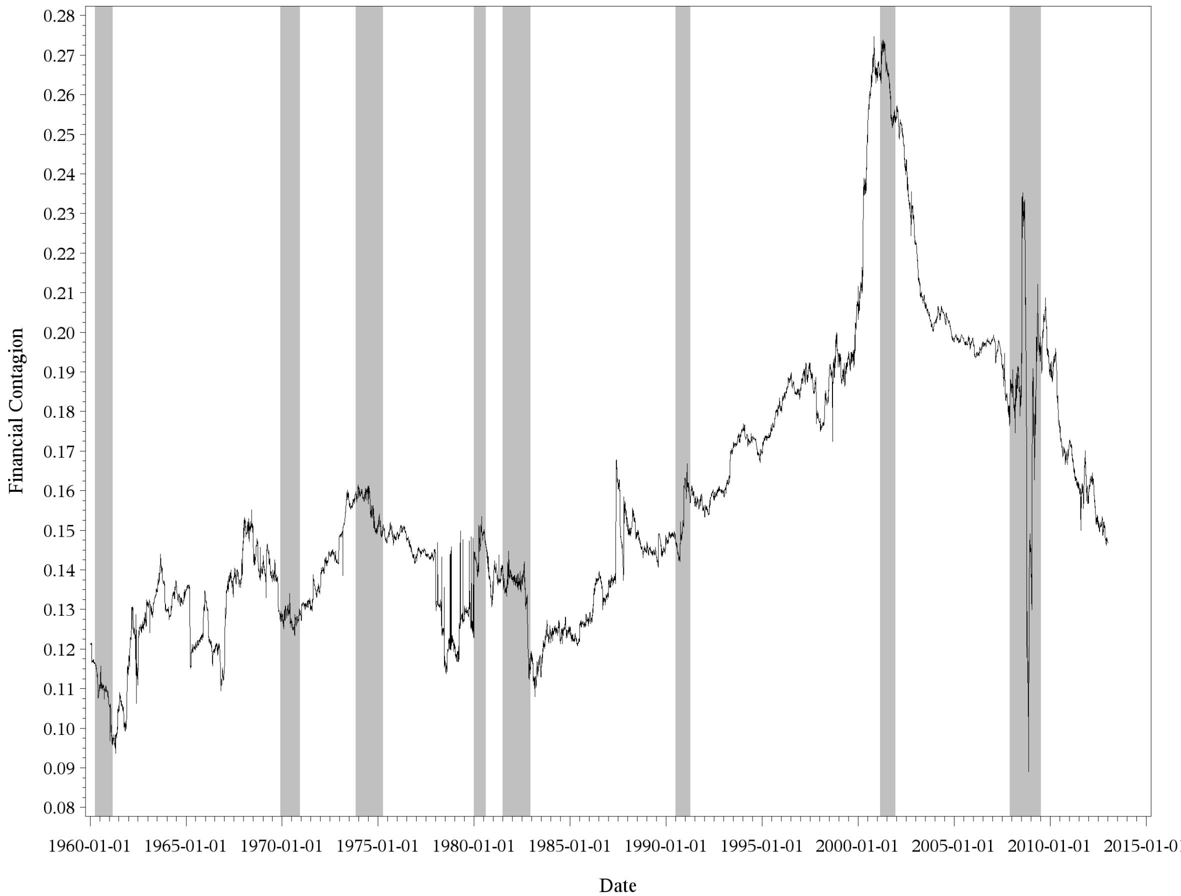


Figure 2.3 Financial Contagion Time Series. This figure plots the time series of financial contagion, FC_t, obtained from eqn. (2.8). Shaded regions are NBER recession dates.

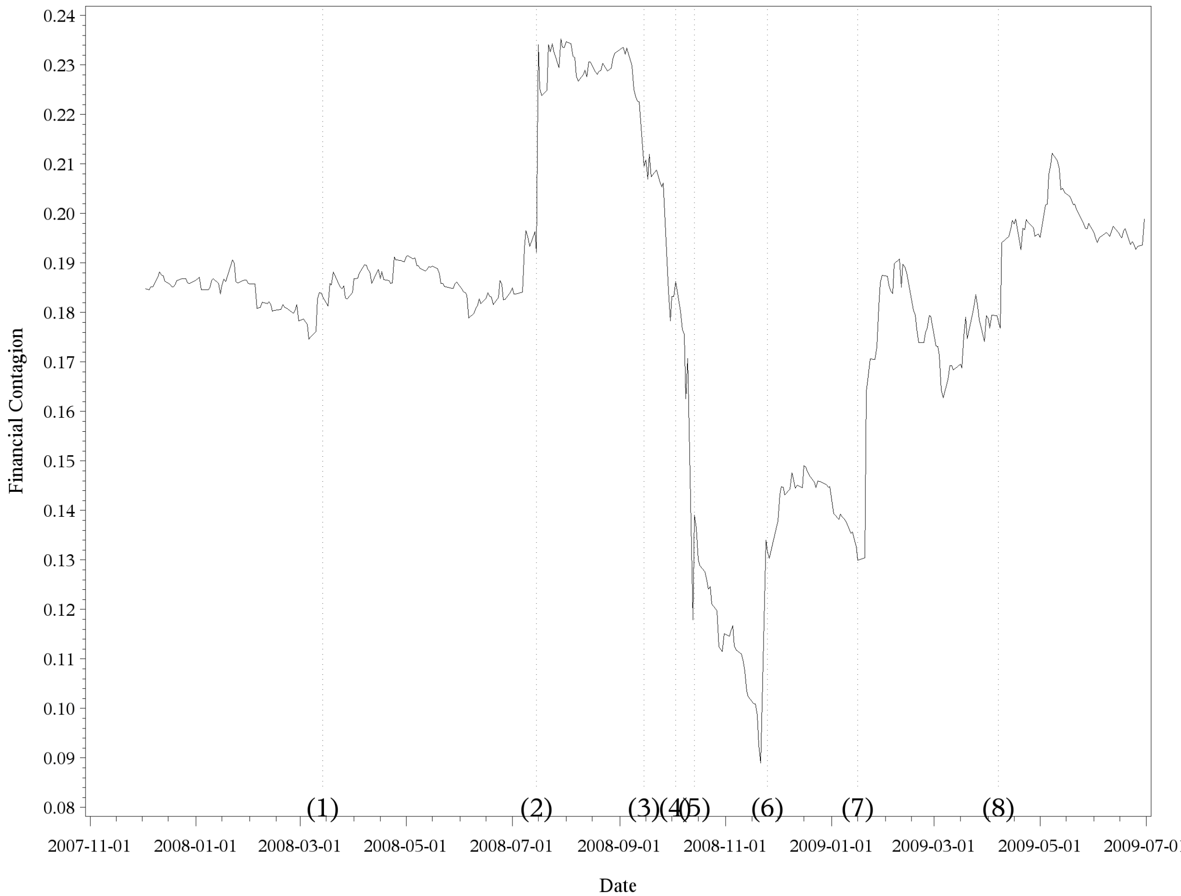


Figure 2.4 Financial Contagion in the 2007-2008 Crisis. This figure plots financial contagion around the time of the 2007-2008 financial crisis, annotated with key economic events. Events are labeled with numbers in parentheses at the bottom of the plot. (1) March 14, 2008: Bear Stearns is bailed out by the New York Federal Reserve and J.P. Morgan, (2) July 15, 2008: SEC emergency order to ban naked short selling in a number of large financial institutions, (3) September 15, 2008: Lehman Brothers files for chapter 11 bankruptcy protection; September 16, 2008: Federal Reserve extends an $85 billion credit facility to American International Group (AIG), (4) October 03, 2008: The Emergency Economic Stabilization Act of 2008, containing the Troubled Asset Relief Program (TARP) is passed by Congress and signed by president Bush, (5) October 14, 2008: The U.S. Treasury announces the TARP program, (6) November 25, 2008: The Term Asset-Backed Securities Loan Facility (TALF) is announced, (7) January 16, 2009: The U.S. government announcement an agreement providing a package of guarantees, liquidity and capital to Bank of America, (8) April 07, 2009: Monthly TARP report is released.

Figure 2.5 Log Wealth Processes. This figure plots the log wealth process for the portfolio that buys the decile of most contagious banks and sells the decile of least contagious banks, with monthly re-balancing. Log wealth processes of the MRKT, SMB, HML, MOM, and LIQ factor portfolios are also plotted. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion bank return factor.

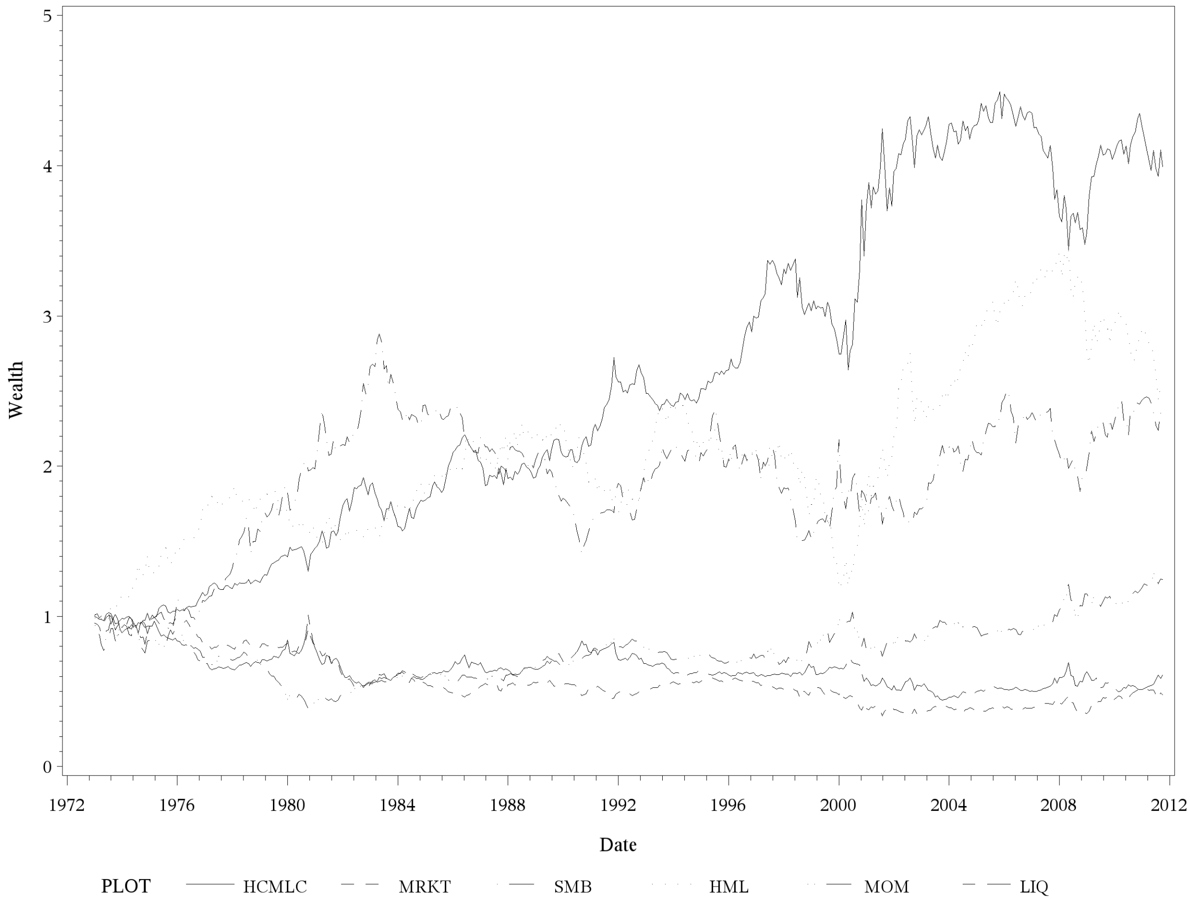


Figure 2.6 Beta-sorted Portfolio Wealth Processes. This figure plots the wealth processes of portfolios that buy the tercile of stocks with greatest factor beta and sell the tercile of stocks with lowest factor beta. Portfolios are rebalanced monthly. Factor betas are estimated from the following rolling regression.

$$
\begin{aligned}
r_{i,t}^{e} = \beta_{i,0} + \beta_{i,MRKT} r_{MRKT,t} + \beta_{i,SMB} r_{SMB,t} + \beta_{i,HML} r_{HML,t} + \beta_{i,MOM} r_{MOM,t} \\
+ \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t}
\end{aligned}
$$

Rolling 60-month regressions are estimated. The previous 60 months of returns are used to estimate betas, portfolios are rebalanced, and portfolio returns are observed in the following month. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion bank portfolio.

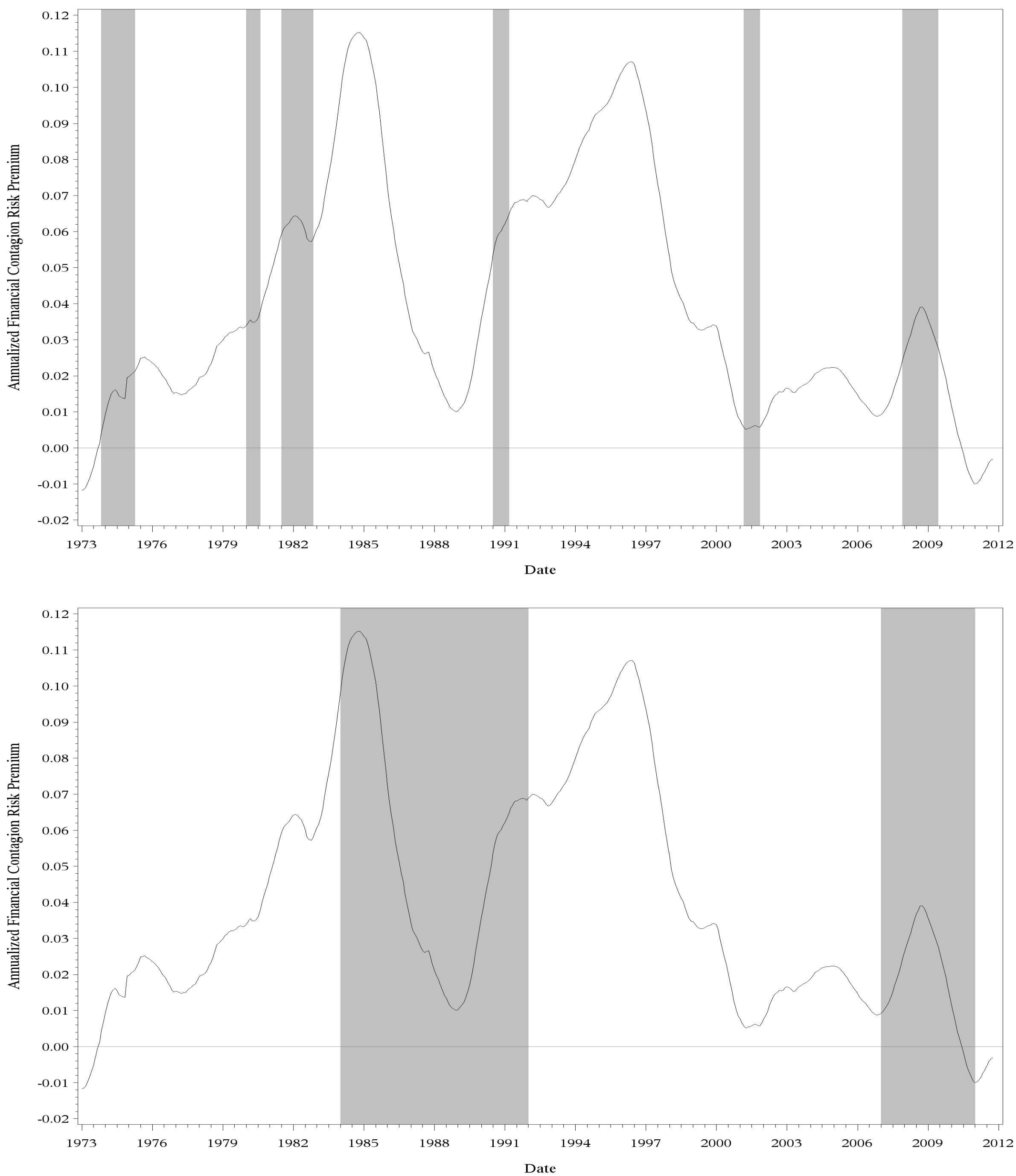


Figure 2.7 Time Series of Financial Contagion Risk Premium. This figure plots the smoothed time series of the estimated financial contagion risk premium, $\widehat{\lambda}_{HCMLC}$, obtained from firm-level Fama-MacBeth regressions as in Table VI. The shaded regions in the top panel are NBER recession dates and the shaded regions in the bottom panel are U.S. banking crises dates from Reinhart and Rogoff (2011). The smoothing procedure used is given by

$$\widehat{\widehat{\lambda}}_{HCMLC} = \sum_{m=-h}^{h} \left[\frac{h+1-|m|}{(h+1)^2} \right] \widehat{\lambda}_{HCMLC}$$

where $h = 23$ (5 percent of the sample size) and the smoothing procedure is run twice.

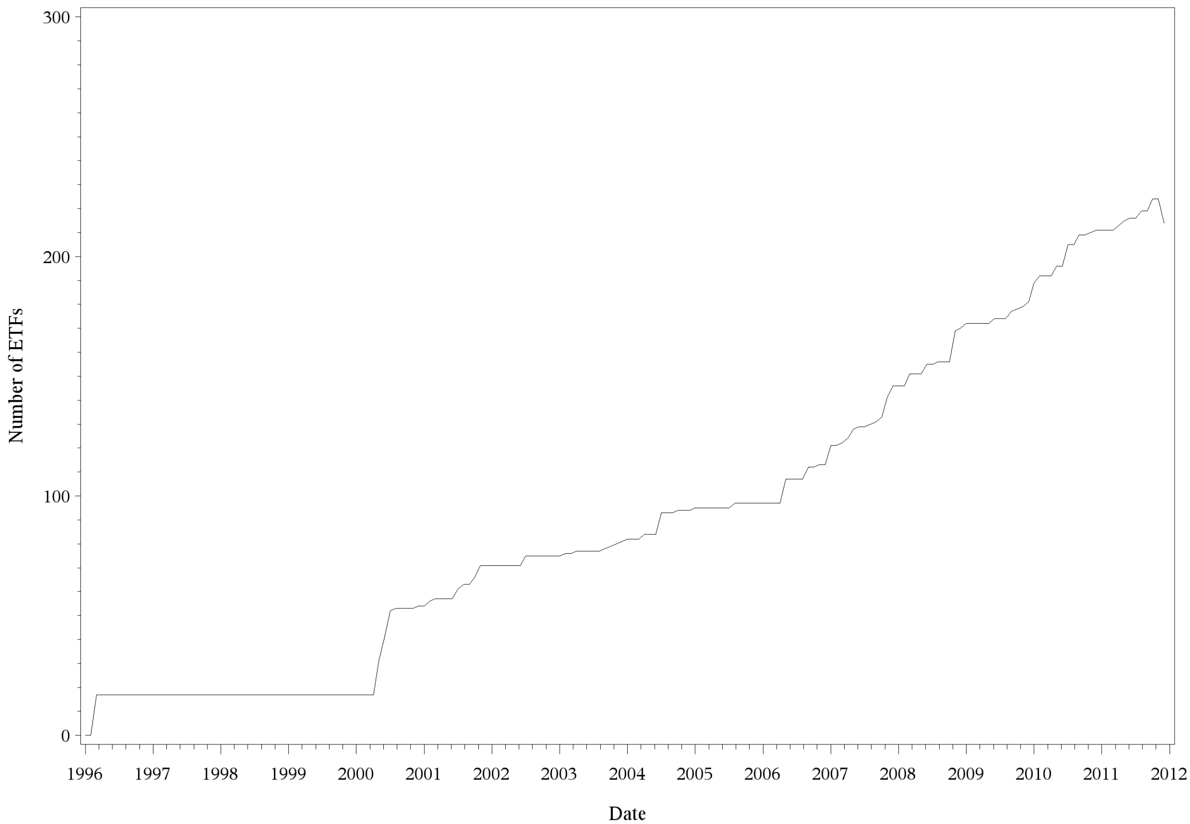


Figure 3.1 ETF Sample Size. This figure presents the time series of the number of ETFs contemporaneously present in the sample.

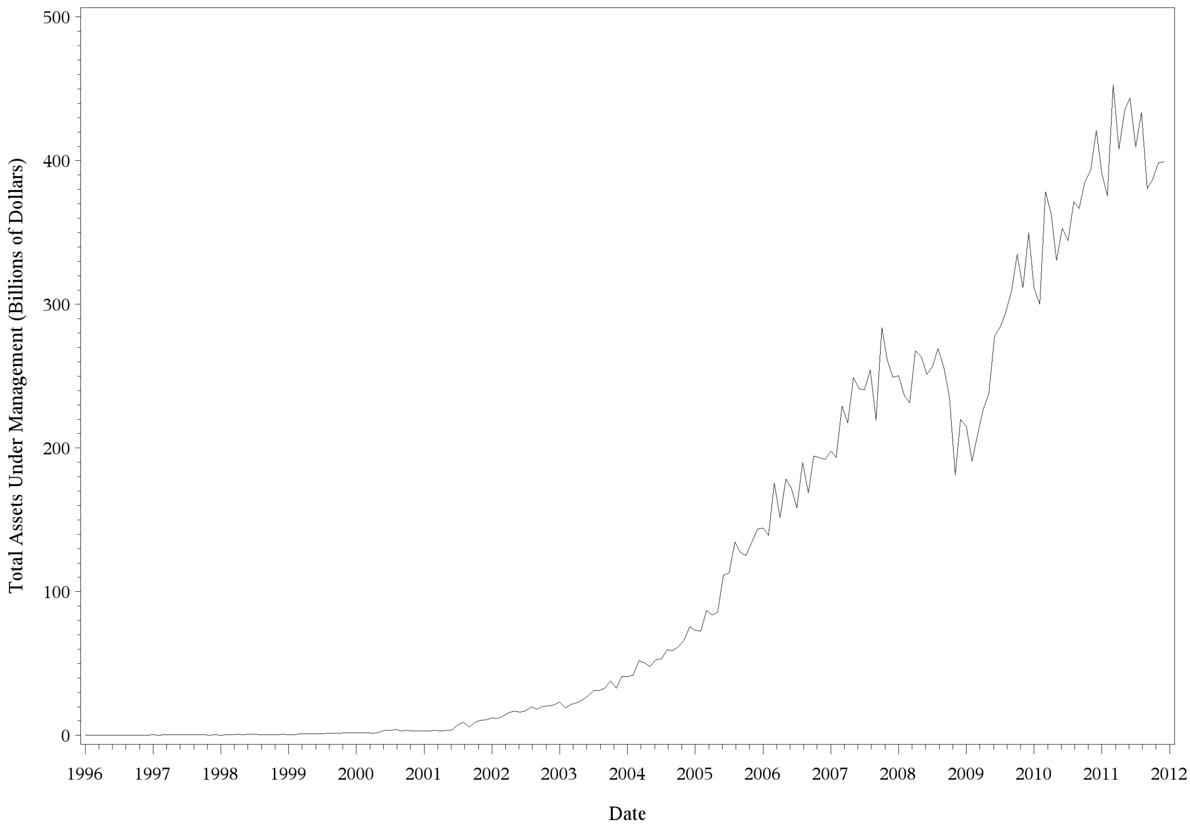


Figure 3.2 ETF Assets Under Management. This figure plots the time series of total assets under management (in billions of dollars) for the ETF sample.

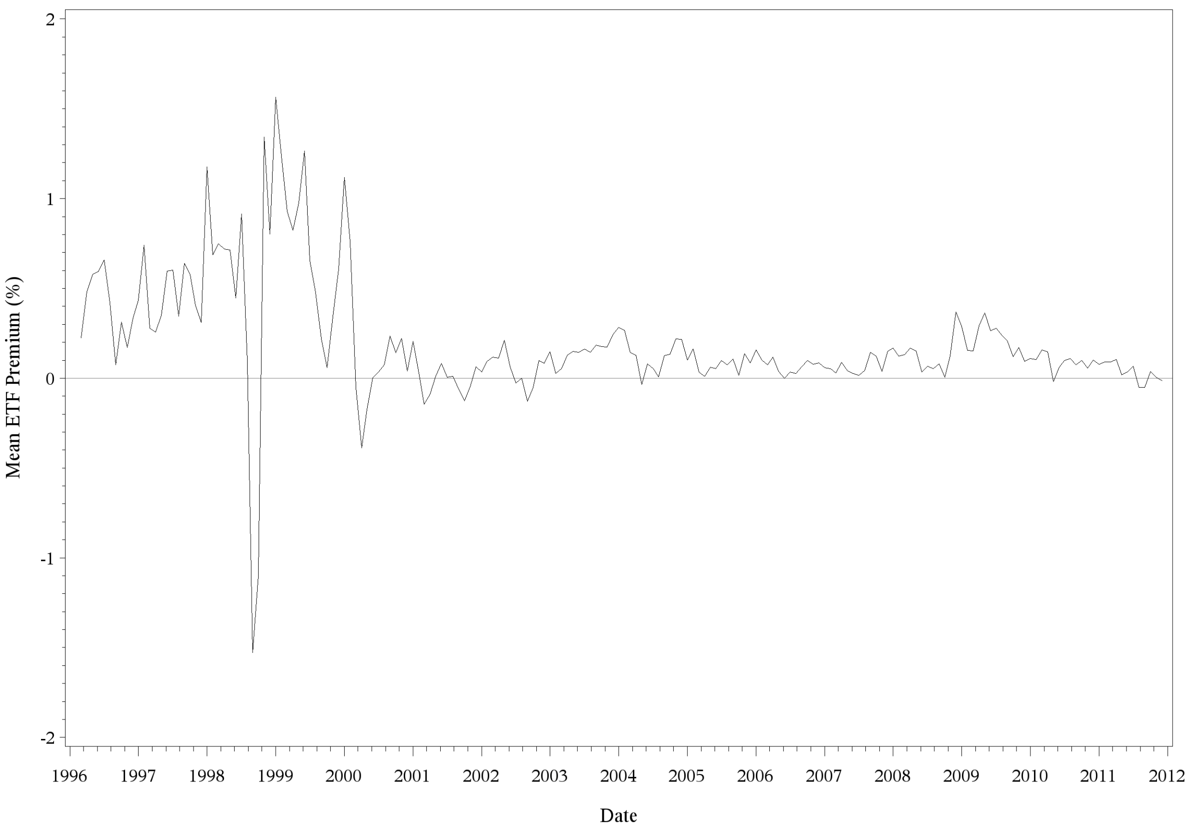


Figure 3.3 Mean ETF Premium. This figure plots the time series of within-month mean premiums across ETFs, $\overline{PREM}_m$. $\overline{PREM}_m$ is defined as

$$PREM_{i,t} = \begin{cases} ln\,(P_{i,t}/NAV_{i,t}) \times 100 & \textit{for domestic ETFs} \\ \widehat{u}_{i,t} \times 100 & \textit{for foreign ETFs} \end{cases}$$

$$\overline{PREM}_m = N_m^{-1} \sum_{i=1}^{N_m} \left[D_{i,m}^{-1} \sum_{t=1}^{D_{i,m}} PREM_{i,t} \right]$$

where $P_{i,t}$ is ETF i's nominal share price, $NAV_{i,t}$ is its net asset value, $\widehat{u}_{i,t}$ is the estimated true premium obtained from eqns. (3.2a,b), N_m is the number of ETFs in the sample in month m, and $D_{i,m}$ is the number of daily observations for ETF i in month m.

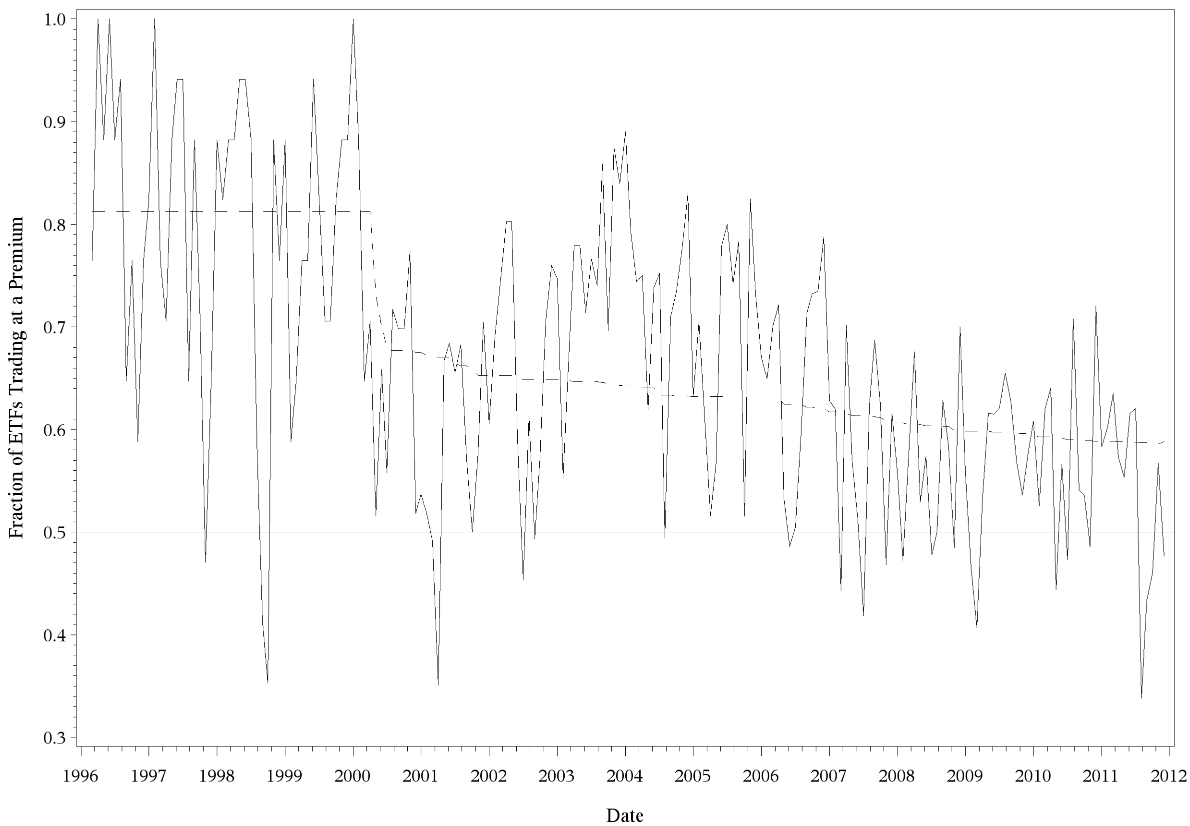


Figure 3.4 Fraction of ETFs Trading at a Premium. This figure plots the time series of the fraction of ETFs with a within-month sample mean premium that is positive (solid line). The dashed line denotes the one-percent critical value for which premiums being equally likely to be positive as negative can be rejected in an unbiased binomial test. Specifically the formula for the critical values (CV), imposing the normal distribution approximation, is

$$CV_m = \frac{N_m p \pm 2.576\sqrt{N_m p\,(1-p)}}{N_m}$$

where N_m denotes the number of ETFs present in the sample in month m, and p is the fraction of ETFs that are expected to be trading at a mean positive premium, if premiums are unbiasead. Therefore, $p = 0.5$.

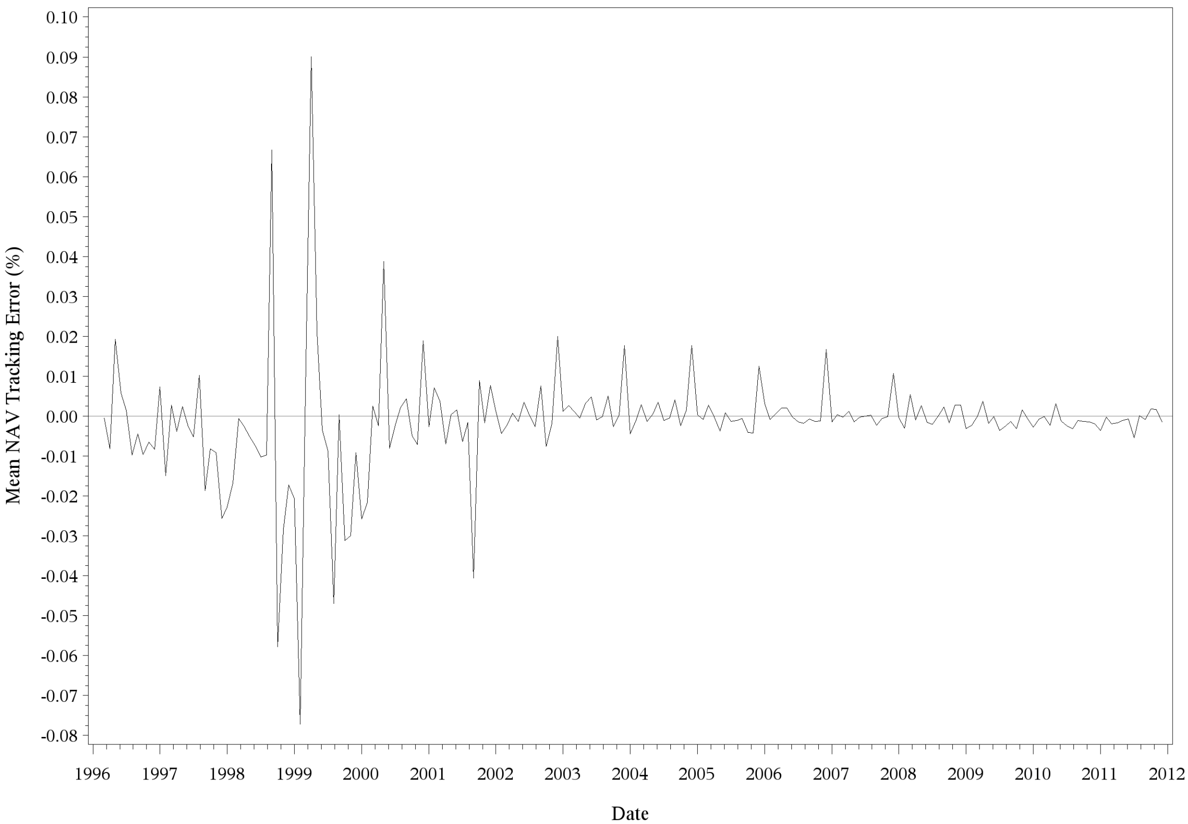


Figure 3.5 Mean tracking errors. This figure plots the time series of within-month mean tracking error across all ETFs, $\overline{TE}_m$. $\overline{TE}_m$ is defined as

$$TE_{i,t} = \left(r_{i,t}^{NAV} - r_{i,t}^{INDEX}\right) \times 100$$
$$\overline{TE}_m = N_m^{-1} \sum_{i=1}^{N_m} \left[D_{i,m}^{-1} \sum_{t=1}^{D_{i,m}} TE_{i,t} \right]$$

where $r_{i,t}^{NAV}$ is ETF i's daily return, $r_{i,t}^{INDEX}$ is the daily return on the index that the ETF aims to replicate, N_m is the number of ETFs in the sample in month m, and $D_{i,m}$ is the number of daily observations for ETF i in month m.

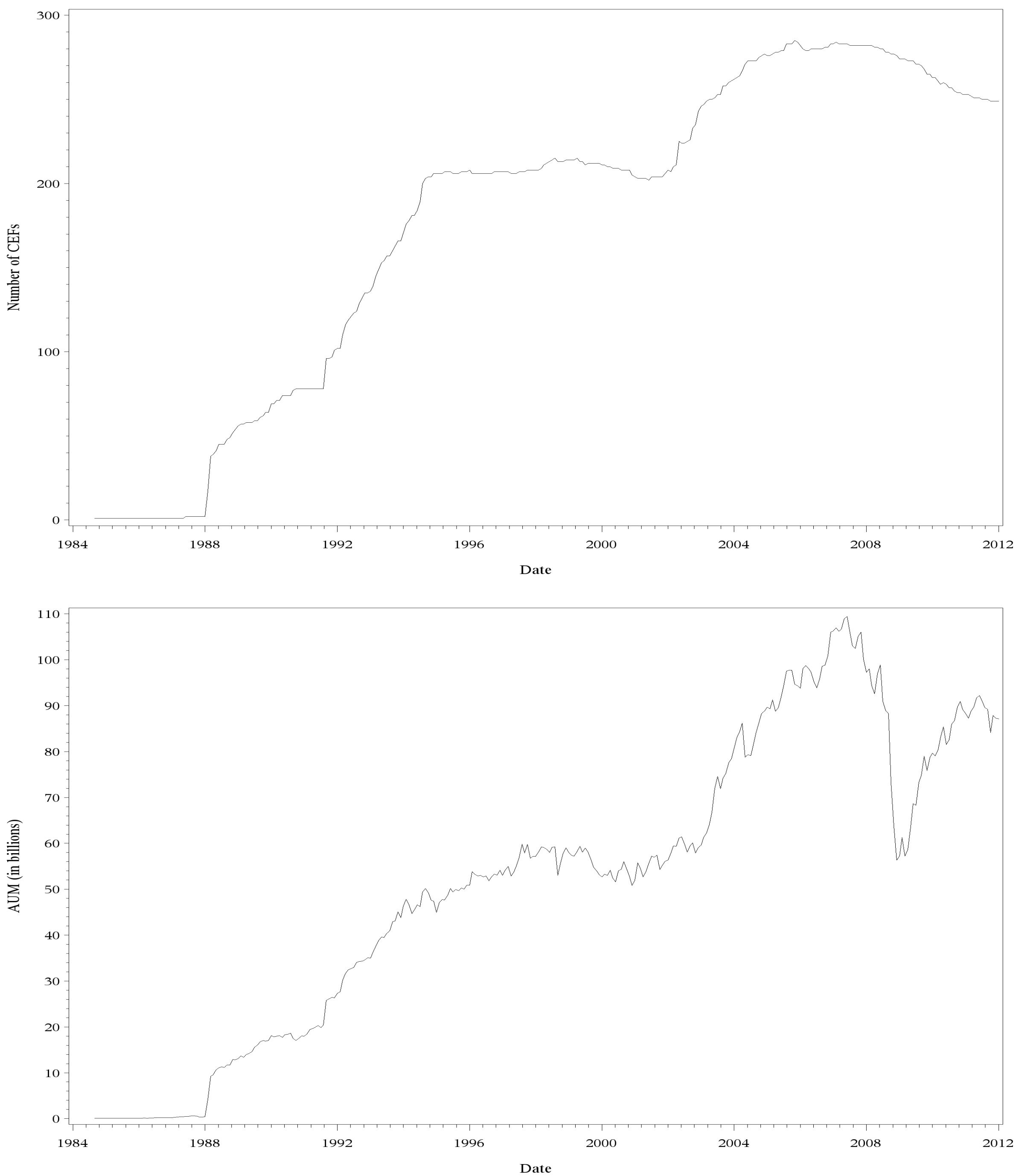


Figure 4.1 Time Series of Closed-End Fund Sample Size. This figure plots the time series of CEF sample size in the top panel and the time series of total market value of the CEF sample in the bottom panel.

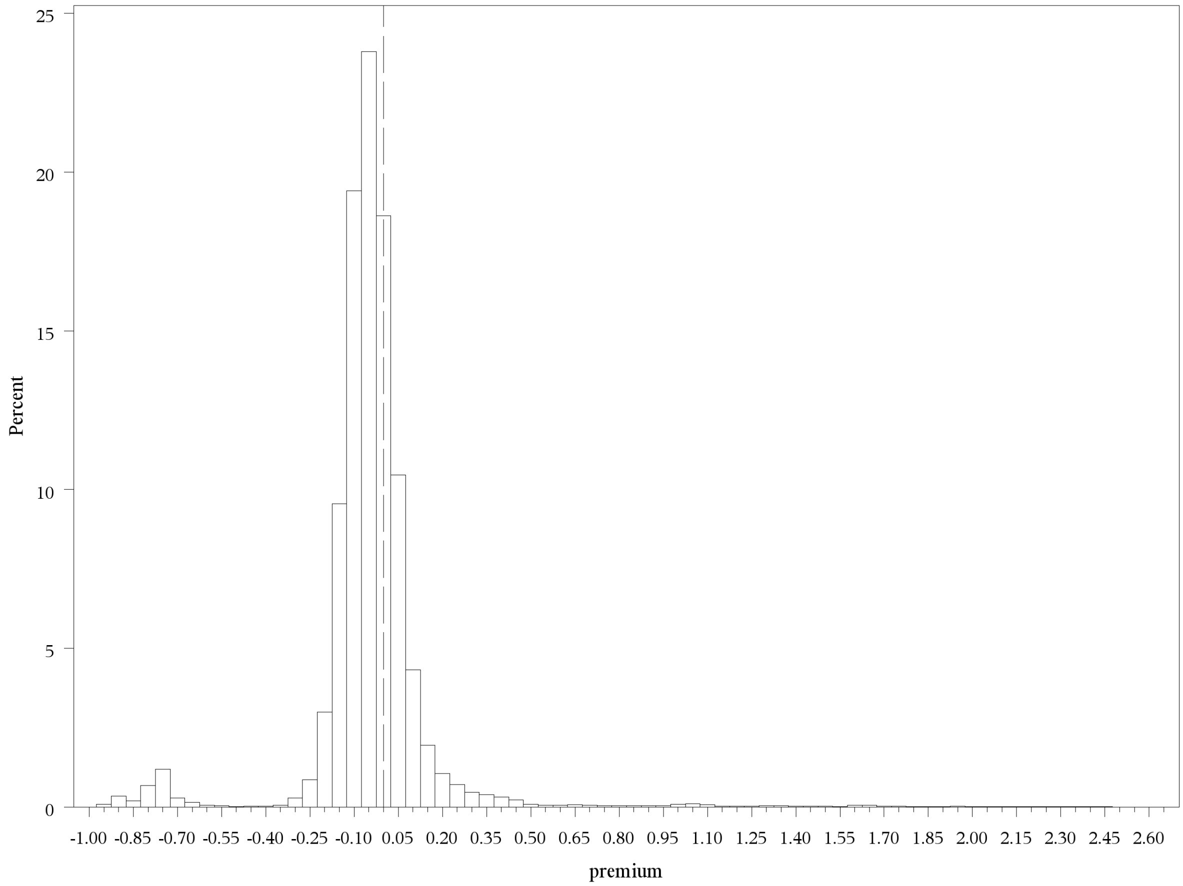


Figure 4.2 Distribution of CEF Premiums. This figure plots the distribution of observations on closed-end fund premiums over the full sample period.

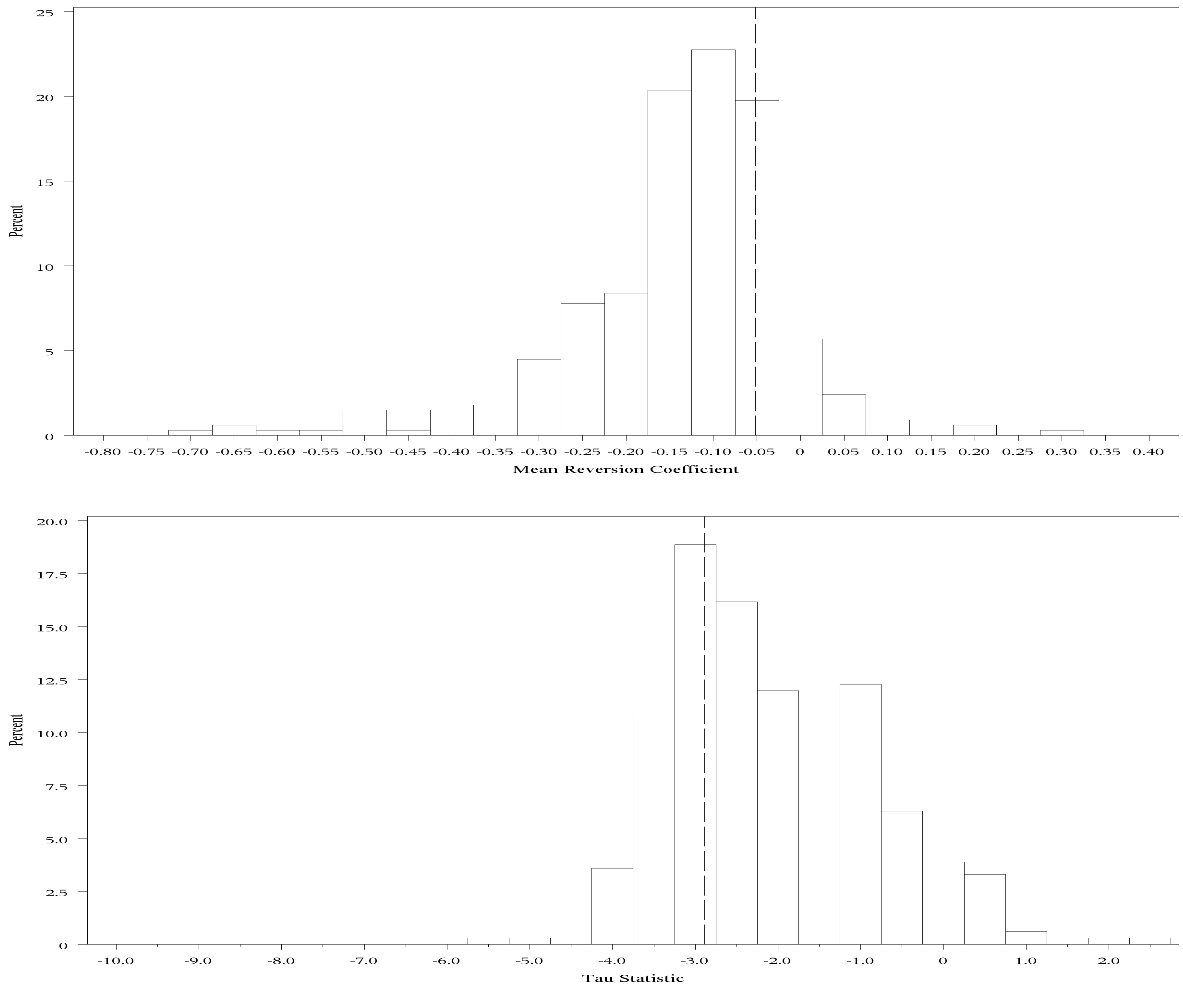


Figure 4.3 T-statistics for Mean Reversion in CEF Premiums and Mean Reversion Parameters. This figure plots histograms of the ADF t-statistics for mean-reversion in CEF premiums and the estimated mean reversion coefficients β_i obtained from estimating the following Augmented Dickey-Fuller regressions:

$$\triangle prem_{i,t} = \alpha_i + \beta_i prem_{i,t-1} + \sum_{j=1}^{k_i} \gamma_{i,j} \triangle prem_{i,t-j} + \varepsilon_{i,t}$$

where $\triangle$ is the difference operator. The optimal lag length, k_i, is chosen using the Campbell and Perron (1991) method. Under the null hypothesis, the mean value of the estimated β_i is -0.052, which is displayed as the dashed line in the top panel. The 5 percent critical value for the null hypothesis of no mean reversion for a sample size of 100 is -2.89, which is displayed as the dashed line in the bottom panel.

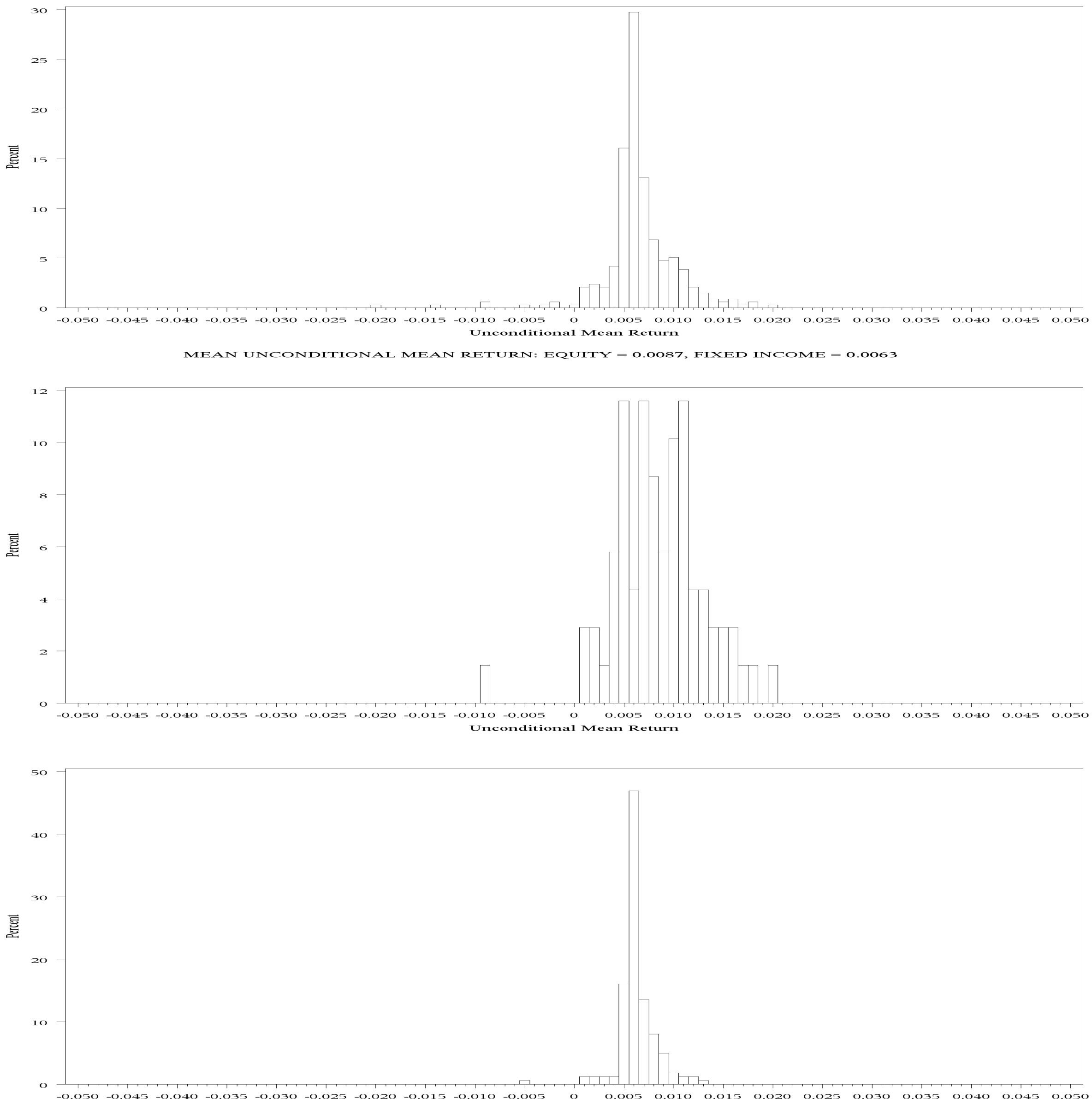
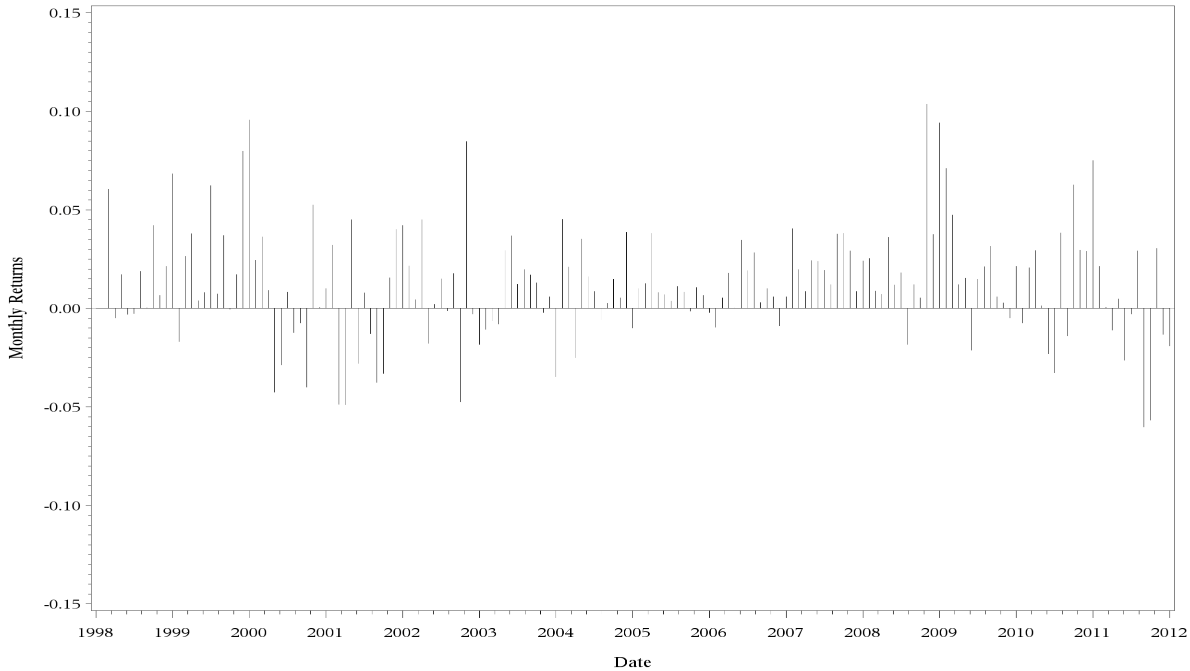


Figure 4.4 CEF Mean Return Distribution. This figure presents the distribution of unconditional monthly mean returns for the closed-end fund sample, in the top panel. MEAN OF MEANS is the mean of unconditional monthly means for equity CEFs and fixed income CEFs, where indicated. The middle panel presents the distribution of unconditional monthly mean returns for the equities closed-end fund sample. The bottom panel presents the distribution of unconditional monthly mean returns for the fixed income closed-end fund sample.



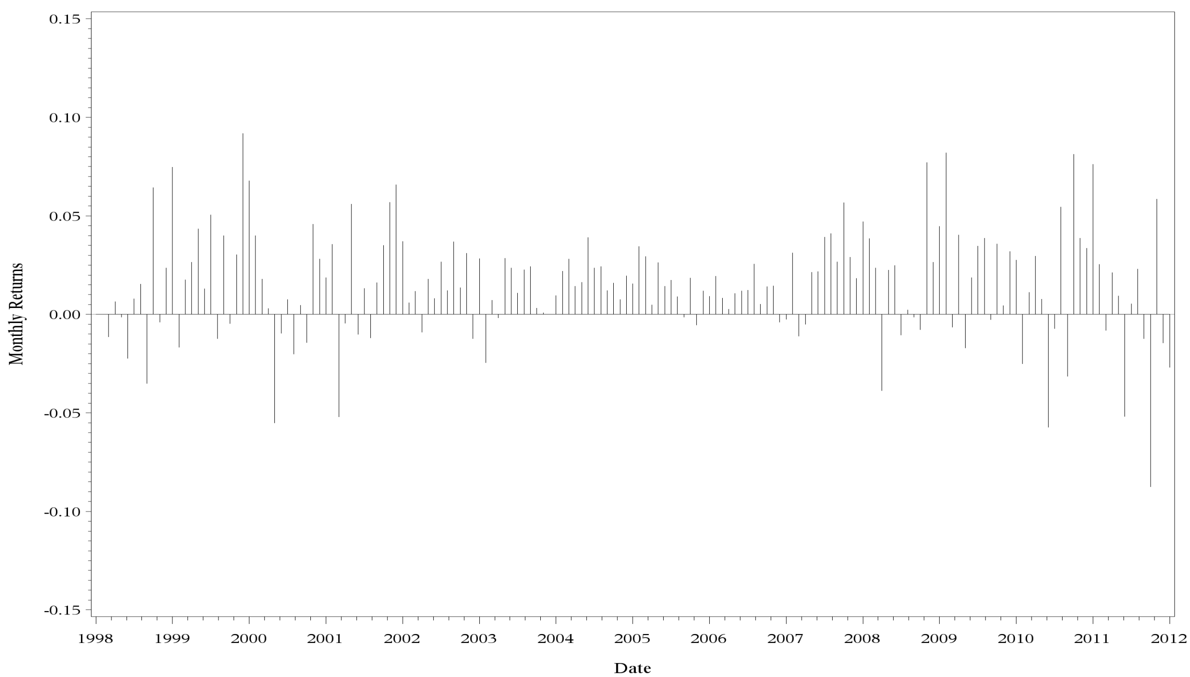


Figure 4.5 Trading Strategy Monthly Returns. This figure plots monthly trading strategy returns for the Q5-Q1 portfolio using the benchmark model (top panel) and the RADF model (bottom panel). Portfolios are equally weighted and rebalanced monthly. The out of sample period is February 1998 to December 2011.

Curriculum Vitae

Academic Employment

Assistant Professor of Finance, University at Albany, SUNY, Albany, NY 12222, 2014-present.

Education

Ph.D. in Finance, Rutgers Business School, Newark, NJ, 2008-May 2014
B.S. in Finance, Auburn University, Auburn, AL, 2004-2008
B.A. in Economics, Auburn University, Auburn, AL, 2004-2008

Research Interests

Empirical asset pricing, market efficiency, and applied time series analysis/econometrics

Awards and Grants

Whitcomb Center for Research in Financial Services Grant, 2013
Dean's Summer Grant, 2010, 2012
Lawrence Fisher Doctoral Research Award, 2010

Professional Affiliations

American Financial Association, European Finance Association, Financial Management Association, Midwest Finance Association, Southwestern Finance Association

Teaching Experience

Corporate Finance (Summer 2009)
Financial Econometrics (Summer 2011 and Summer 2012)
Futures and Options (Summer 2010, Fall 2011, Fall 2012, and Summer 2013)
International Financial Management (Spring 2012)

Conference Participation

Global Finance Conference, Monterey Bay, CA, May 2013, "Currency Pricing Errors and Customer Trade".

Financial Management Association Doctoral Student Consortium, Chicago, IL, October 2013, "Financial Contagion Risk and the Stochastic Discount Factor".

Southwestern Finance Association Annual Conference, Dallas, TX, March 2014, "Financial Contagion Risk and the Stochastic Discount Factor".

Midwest Finance Association 2014 Annual Meeting, Orlando, FL, March 2014, "Financial Contagion Risk and the Stochastic Discount Factor".

Refereeing

Review of Quantitative Finance and Accounting