Carbon Portfolio Management

Alexander Afonin
University College Dublin [*]

Don Bredin
University College Dublin[†]

Keith Cuthbertson
City University[‡]

Cal Muckley
University College Dublin[§]

Dirk Nitzsche
City University[¶]

Abstract

The aim of the European Union's Emissions Trading Scheme (ETS) is that by 2020, emissions from sectors covered by the EU ETS will be 21% lower than in 2005. In addition to large CO_2 emitting companies covered by the scheme, other participants have entered the market with a view to using emission allowances for the diversification of their investment portfolios. The performance of this asset as a stand alone investment, as well as its portfolio diversification implications will be investigated in this paper. Our results indicate that the market views Phase 1, Phase 2 and Phase 3 EUA futures as unattractive as stand alone investments. In a portfolio context, in Phase 1, once the short-selling option is added, there are considerable portfolio benefits. However, our results indicate that these benefits only existed briefly during the pilot stage of the EU ETS. There is no evidence to suggest portfolio diversification benefits exist for Phase 2 or the early stages of Phase 3.

Keywords: CO_2 emissions allowances, Futures, Emissions trading, Energy, Kyoto Protocol.
JEL Classification: G13, G14, G19.

[*]E-mail: alexander.afonin@ucd.ie
[†]E-mail: don.bredin@ucd.ie
[‡]E-mail: K.Cuthbertson@city.ac.uk
[§]E-mail: cal.muckley@ucd.ie
[¶]E-mail: d.nitzsche@city.ac.uk. Corresponding author: Dirk Nitzsche, Cass Business School, City University, London, United Kingdom. The authors are grateful for funding support from Science Foundation Ireland (SFI) under Grant Number 16/SPP/3347.

1 Introduction

In January 2013 Phase 3 of the EU ETS was introduced. The EU ETS is a cap-and-trade scheme that issues a restricted amount of emission allowances, also known as European Union allowances (EUAs), to companies on an annual basis. Each EUA represents the right to emit 1 metric tonne of carbon dioxide. At the end of each year companies must hold the required amount of emission allowances to meet their emissions over the previous year. The scheme covers firms operating in the power sector, cement and ferrous metal producers and all combustion facilities with a generating capacity of 20 MW, or more. Airlines joined the scheme in January 2012.[1] The ETS allows firms to trade the amount of emission permits that they hold and as a result has applied a market value to this asset. Phase 1 of the EU ETS operated between 2005 and 2007, with Phase 2 running from 2008 to 2012 and Phase 3 extending from 2013 to 2020.[2] Since its inception in 2005 the EU ETS has become the world's largest emissions market.[3]

The introduction of global emission trading markets and their rapid growth resulted in the establishment of emission allowances as a new financial asset. The growth of the carbon markets has mainly been as a result of the involvement of other investors, including hedge funds, pension funds, carbon funds, foundations, and other plan sponsors.[4] These investors have no emission reduction obligations and participate in the carbon markets in order to extend their investment opportunities through diversification. In the last decade there has been considerable interest in carbon markets from both researchers and practitioners and this is reflected in a flood of new empirical studies focusing on the portfolio management implications of carbon assets. Studies include Mansanet-Bataller and Pardo (2008), Chevallier (2009), Afonin *et al.* (2012), Reboredo (2013) and Reboredo and Ugando (2015).[5] One of the earliest studies is Mansanet-Bataller and Pardo (2008), which examines the investment

[1]Current policy has limited the scope of the EU ETS to flights within the European Economic Area (EEA), to support the development of a global measure by the International Civil Aviation Organization (ICAO).

[2]Ellerman *et al.* (2014) provides an excellent review of the EU ETS during Phase 1 and 2.

[3]According to PointCarbon (2012), 8 billion metric tonnes of emission allowances were traded on EU ETS in 2011 - a 19% increase compared to 2010 figures.

[4]Examples include RNK Capitial, a New York based hedge fund with an emissions focus and Citadel Investment Group. See Labatt and White (2007) and Lucia, Mansanat-Bataller and Pardo (2015) for further example.

[5]Both Reboredo (2013) and Reboredo and Ugando (2015) highlight the benefits of EU allowances in relation to diversification of market risk and the reduction of downside risk reduction in crude oil markets. Similar arguments are made by Börger *et al.* (2009).

characteristics of EU ETS futures both as a sole investment and as part of a diversified portfolio. The authors investigate the properties of EUA futures prices for Phase 1 and Phase 2 of the EU ETS, coupled with energy variables such as brent and natural gas, as well as equities and bonds.[6] Their main findings indicate that both Phase 1 and Phase 2 EUA futures are unattractive as a stand-alone investment, but that including CO_2 EUA futures in an already diversified portfolio can improve the investment opportunity set. Chevallier (2009) performs mean-variance optimization and analyzes the efficient frontier for diversified portfolios that include carbon assets. The range of asset classes include equity, fixed income, oil and natural gas, along with weather variables, coal and a risk-free asset in the form of the US Treasury bills. The author finds that a diversified portfolio can achieve an expected return of 3% with standard deviation less than 0.06% by including carbon assets. The results from Afonin *et al.* (2012) are generally consistent with Mansanet-Bataller and Pardo (2008) and Mansanet-Bataller (2011). The authors find that the market views both Phase I and early sample Phase II EUA futures as unattractive as stand alone investments.

The standard approach used in the literature to analyze the diversification potential of an asset class is to consider two types of portfolios. The first, a benchmark portfolio would include the 'standard' asset classes such as stocks and bonds. The second, an alternative extends the standard portfolio by adding the new asset class in question. The mean-variance optimization is performed for both portfolio types and the performances of the standard and alternative efficient portfolios are compared. The mean and the covariance matrix of asset returns that are used as inputs for the optimization problem are generally not known and need to be estimated from historical data. The issue of the sensitivity of portfolio allocations to the estimation error has been examined by a number of studies, see Jobson and Korkie (1980) and Michaud (1989). The main implication of the estimation error is the poor out-of-sample performance of mean-variance efficient portfolios constructed from sample data. Various robust optimization techniques have been proposed to address this issue. Michaud (1998) develops a bootstrap based resampling mechanism, Jorion (1986) suggests to use Bayes-Stein shrinkage estimator for the mean and Ledoit and Wolf (2004b) introduce a shrinkage estimator for the covariance matrix. Empirical research conducted by these authors indicates that portfolios constructed using robust methods are better

[6] This study has been extended by one of the authors up to 2010 in Phase 2. The results are generally consistent with those reported in the original paper, see Mansanet-Bataller (2011).

diversified and outperform their sample counterparts.

Our paper significantly develops the literature on carbon portfolio management and extends the previous research on diversification effects of carbon assets in several ways. First, we examine a much richer benchmark portfolio of assets and one that takes account of the research in the general portfolio management literature. Second, our analysis covers the complete history of the EU ETS Phase 1 and 2, and up to mid-2015 for Phase 3. Third, we provide a detailed assessment of asset allocations and present formal tests to compare portfolio performance using the Jobson-Korkie test and the robust bootstrapping method of Ledoit-Wolf. Finally, we also conduct a series of complementary sensitivity analyses using mean variance spanning tests (Huberman and Kandel, 1987 and Kan and Zhou, 2012).

Our results are informative for both policy makers and practitioners alike. We find considerable portfolio benefits of augmenting a standard portfolio with carbon, but only allowing short-sales and most importantly only for Phase 1, the pilot of the EU ETS. For policy makers the results indicate a marked difference between the Pilot Phase and the Kyoto Phase (and Phase 3). In particular the results indicate evidence of market development as indicated by a rise in the common performance behaviour of EUAs relative to other asset classes. Our results are consistent with the results reported using fundamentals based models of the EU ETS (see Bredin and Muckley, 2011). For practitioners, the results indicate that the *emerging* nature of the asset class represented portfolio benefits during Phase 1, but with the maturing of the market (during the Kyoto Phase and in Phase 3) these benefits have been eliminated.

The remainder of the paper is organized as follows. Section 2 provides a review of the relatively limited academic literature on carbon portfolio implications. Section 3 outlines the methodology employed to analyze diversification effects of EUA futures, while section 4 describes the data set used for the empirical study and presents the results. Conclusions are provided in section 5.

2 Alternative Assets, Portfolio Selection and Emission Allowances

Since the seminal work by Markowitz (1952) the issue of adding new assets to a portfolio and the affects on portfolio performance has received a lot of academic and practitioner attention. Jensen *et al.* (2000) examined portfolios that can invest in stocks, corporate bonds, Treasury-bills, REITs and the commodity futures over the period 1973 to 1997. They found that, depending upon risk tolerance, commodities should represent anywhere from 5-36% of investors' portfolios. Erb and Harvey (2006) also studied commodity futures in a portfolio context. Their analysis showed that a long-only allocation to commodities does not yield equity-like return. On the other hand, they provided evidence that there are benefits to an asset allocation overlay that tactically allocates using commodity futures exposures. The authors examined several trading strategies that use both momentum and the term structure of futures prices. The results suggested that the tactical strategies provide higher average returns and lower risk than a long-only commodity futures exposure.

The literature on portfolio management with carbon assets is in a phase of rapid development. The first study of EU ETS emission allowances and portfolio management has been completed by Mansanet-Bataller and Pardo (2008). The authors investigated the properties of EUA futures prices for Phase 1 and the beginning of Phase 2. They found that both Phase 1 and Phase 2 EUA futures contracts are unattractive as a sole investment due to their negative returns and high volatility. The authors pointed out that investors that took short positions in these contracts assumed high risk but also received high returns. The paper looked at EUA futures in the context of a multi-asset portfolio comprising futures on Dow Jones Euro Stoxx 50, Euro Schatz, Bolb and Bund futures and Brent and Natural Gas futures. Using both historical and risk-adjusted returns the authors show that Phase 1 and Phase 2 EUA futures can improve the investment opportunity set for an investor that initially invests in traditional assets such as stocks and fixed income. Mansanet-Bataller (2011) extends the sample up to November 2010, but finds relatively consistent results to those reported in Mansanet-Bataller and Pardo (2008).

Chevallier (2009) also examines portfolio management for the case of December 2008 expiration Phase 2 EUA futures. That paper extended results of Mansanet-Bataller and

Pardo (2008) by performing portfolio optimization on a wider set of asset classes that in addition to equity, fixed income, oil and natural gas, also includes weather variables, coal and risk-free asset in the form of US Treasury-Bills.[7] Chevallier indicates that a global portfolio consisting of energy (including carbon), weather, bond and equity and as well as a risk free asset achieves a level of standard deviation less than 0.06% for an expected return of 3%. Furthermore, the conducted regression analysis, suggests that the EUA futures delivered positive statistically significant *alpha*, making these instruments an attractive diversification tool.

Turning to more recent work, Afonin *et al.* (2012) examine allocations to Phase I EUA futures in optimal portfolios and find the benefits are small and there is no statistically significant difference in the risk adjusted excess returns between standard benchmark portfolios and portfolios extended to include EUAs. The authors only have a relatively small sample of data from Phase 2. They show evidence of portfolio performance improvement for the case of minimum variance portfolios only. There was no performance improvement for tangency portfolios. The results reported by Afonin *et al.* (2012) are, hence, very much consistent with those reported by Mansanet-Bataller and Pardo (2008) and Mansanet-Bataller (2011).

3 Methodology

3.1 Portfolio Introduction

The question of how an asset type affects mean-variance characteristics of an already diversified portfolio has been studied extensively. Jensen *et al.* (2000), for example, studied the diversification effects of commodity futures. Amin and Kat (2003) analyzed the diversification affects of including hedge funds. The conventional approach used in the literature is to consider two types of portfolios. The first portfolio type consists of 'standard' asset classes such as stocks and bonds. The second portfolio type extends the standard portfolio by adding the new asset class in question.

In our case the standard portfolio consists of the following asset classes: European equities, European government and corporate bonds, crude oil, natural gas and non-energy

[7] As well as EU allowances, Chevallier (2009) also examines Certified Emission Reductions (CERs).

commodities. The extended portfolio also includes Phase 1, Phase 2 or Phase 3 EUA futures. For each phase a rolling window optimization is performed. Asset allocations are recalculated on a quarterly basis using historical returns within a rolling 6 month window. During each optimization process the following portfolio types are constructed:

- **GMV** - Global Minimum Variance Portfolio based on sample covariance matrix
- **GMV-LW** - Global Minimum Variance Portfolio using Ledoit-Wolf covariance shrinkage estimator
- **TP** - Tangency Portfolio based on sample mean and sample covariance matrix
- **TP-BS** - Tangency Portfolio estimated using Bayes-Stein mean shrinkage estimator and sample covariance matrix
- **TP-LW** - Tangency Portfolio estimated using sample mean and Ledoit-Wolf covariance shrinkage estimator
- **TP-BS-LW** - Tangency Portfolio based on Bayes-Stein mean shrinkage estimator and Ledoit-Wolf covariance shrinkage estimator
- **NP** - Naive Portfolio that uses the same allocation for all assets[8]

Both the standard and the extended portfolio are constructed for each of the above types. Portfolio optimization is performed with both short and no short-selling constraints.[9] To answer the question of how EUA futures affect already diversified portfolios, we compare the performance of standard and extended portfolios using the Jobson-Korkie test, as well as using the robust Sharpe ratio test proposed by Ledoit and Wolf (2008).[10] Finally, the robustness of our analysis is examined using a mean variance spanning test (Huberman and Kandel, 1987 and Kan and Zhou, 2012).

[8] The benefits of the naive portfolio, in terms of out-of-sample performance, have been highlighted by DeMiguel *et al.* (2009).

[9] DeMiguel *et al.* (2013) show that using option-implied volatility, risk premium, and skewness to adjust expected returns can improve the portfolio Sharpe ratio, even after prohibiting short sales and accounting for transaction costs. We leave this aspect of carbon portfolio optimization, availing of informion inherent in financial derivatives, to future work.

[10] DeMiguel *et al.* (2009a) proposed a more generic framework for finding portfolios that perform well out-of-sample. Their method is based on solving the standard mean-variance optimization problem with an additional constraint on the norm of the weights vector. The study shows that using different definitions for the vector norm is equivalent to the Ledoit-Wolf shrinkage mechanism.

3.2 Portfolio Selection Problem

Markowitz (1952) introduced modern portfolio theory and the mean-variance analysis for constructing optimal portfolios. The starting point of the theory is that an investor at time t decides what portfolio of securities to hold until time $t+\Delta t$ based on the expected gains or losses at time $t+\Delta t$. This is a so called one-period optimization problem. Several challenges are associated with the use of classical mean-variance optimization. The first difficulty is that unconstrained optimization often results in corner solutions (see, Fabozzi *et al.*, 2006). Assets with high return and low risk receive large allocations, while assets with low return and high risk receive small allocations in the optimal portfolio. As a result, the optimal portfolio is not fully diversified and is exposed to ex-post risk. A common approach to address this problem is to impose constraints on the optimal asset allocations (see Chopra (1993) for example). The difficulty with this approach, is the *ad-hoc* nature of the chosen constraints. An additional complexity in the application of mean-variance analysis is that the standard asset allocations are very sensitive to estimation errors in expected returns and the covariance matrix. The effects of parameter uncertainty on portfolio allocations has been highlighted by a number of studies, e.g. see, Merton (1980), while Chopra and Ziemba (1993) found that the estimated allocations are particularly sensitive to variations in the means.

3.3 Robust Optimization

Jorion (1985) proposes Bayes-Stein shrinkage estimators to *shrink* the means of assets towards a global mean, in order to reduce the extent of extreme variations, when using the sample mean as an input. In general, the estimator can be defined in the following form:

$$E(\bar{r}) = w\bar{r}_g + (1-w)\bar{r} \tag{1}$$

where $E(\bar{r})$ is the adjusted mean estimate, $\bar{r}_g$ - global mean, $\bar{r}$ - assets mean and w is the shrinkage factor. Jorion (1985) showed that given a suitable prior, the shrinkage factor can be estimated as follows:

$$\hat{\lambda} = \frac{(N+2)(T-1)}{(\bar{r}-r_g I)' S^{-1} (\bar{r}-r_g I)(T-N-2)} \tag{2}$$

$$\hat{w} = \frac{\hat{\lambda}}{\hat{\lambda} + T} \tag{3}$$

where T is the sample size, N is the number of assets, S is the covariance matrix, r_g is the mean return of the minimum variance portfolio and I is the vector of ones. In this paper we adopt the Bayes-Stein shrinkage estimator for the mean of asset returns.

Ledoit and Wolf (2003) have highlighted the estimation errors associated with simply using historical data to calculate the sample covariance matrix. Drawing on the literature on estimation errors in the means, Ledoit and Wolf (2004a) propose a shrinkage estimator as a replacement for the sample covariance matrix. The proposed shrinkage estimator has the following form:

$$\delta F + (1 - \delta) S \tag{4}$$

where $0 \leq \delta \leq 1$, S is the sample covariance matrix and F is a highly structured estimator known as shrinkage target. The sample covariance matrix is shrunk towards the highly structured estimator. δ is referred to as shrinkage constant or shrinkage intensity. The shrinkage constant is given by:

$$\delta = max(0, min(\frac{k}{T}, 1)) \tag{5}$$

where T is the sample size and

$$k = \frac{\pi - \rho}{\gamma}, \tag{6}$$

$$\pi = \sum_{i=1}^{N} \sum_{j=1}^{N} \pi_{ij}, \pi_{ij} = \frac{1}{T} \sum_{t=1}^{T} ((y_{it} - \bar{y_{i.}})(y_{jt}) - \bar{y_{j.}}) - \sigma_{ij})^2, \tag{7}$$

$$\rho = \sum_{i=1}^{N} \pi_{ii} + \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} \frac{\bar{r}}{2} (\sqrt{\frac{\sigma_{jj}}{\sigma_{ii}}} \eta_{ii,ij} + \sqrt{\frac{\sigma_{ii}}{\sigma_{jj}}} \eta_{jj,ij}), \tag{8}$$

$$\eta_{ii,ij} = \frac{1}{T} \sum_{t=1}^{T} (((y_{it} - \bar{y_{i.}})^2 - \sigma_{ii})(y_{it} - \bar{y_{i.}})(y_{jt} - \bar{y_{j.}}) - \sigma_{ij}), \tag{9}$$

$$\eta_{jj,ij} = \frac{1}{T}\sum_{t=1}^{T}(((y_{jt} - \bar{y_{j.}})^2 - \sigma_{jj})(y_{it} - \bar{y_{i.}})(y_{jt} - \bar{y_{j.}}) - \sigma_{ij}), \tag{10}$$

$$\gamma = \sum_{i=1}^{N}\sum_{j=1}^{N}(f_{ij} - \sigma_{ij})^2 \tag{11}$$

Ledoit and Wolf (2003, 2004a,b) propose various shrinkage targets including the constant correlation model, the single index model and the two-parameter model.

3.4 Portfolio Performance Comparison

To compare performance of two portfolios we use the Jobson and Korkie (1980) test of the equality of Sharpe ratios. In the corrected version, Memmel (2003) states the test statistic as having the following form:

$$z = \frac{(r_1 - r_f)\sigma_2 - (r_2 - r_f)\sigma_1}{\sqrt{\frac{1}{T}(2\sigma_1^2\sigma_2^2 - 2\sigma_1\sigma_2\sigma_{12} + \frac{1}{2}r_1^2\sigma_2^2 + \frac{1}{2}r_2^2\sigma_1^2 - r_1r_2\sigma_{12}^2/\sigma_1\sigma_2)}} \tag{12}$$

where r_1, σ_1, r_2, σ_2 are mean and standard deviation of return from portfolio 1 and 2 respectively, r_f is the risk-free return and σ_{12} is the covariance of returns from portfolio 1 and 2. Jobson and Korkie (1980) indicated that the z statistic is asymptotically standard normal. Significant positive z values can be viewed as the indication that portfolio 1 outperforms portfolio 2. The derivation of the test statistic in equation 12 is based on the assumption that the portfolio return distribution is normal. This assumption however rarely holds in practice.

Ledoit and Wolf (2008) suggested a robust portfolio performance hypothesis test based on the Sharpe ratio. The authors propose a studentized time series bootstrap confidence interval. If the differences below are within the confidence interval, then they are no different to zero.

Ledoit and Wolf (2008) define

$$\Delta = \frac{\mu_1}{\sigma_1} - \frac{\mu_2}{\sigma_2} \tag{13}$$

where $\mu_{1(2)}$ and $\sigma_{1(2)}$ are mean and standard deviation of excess returns of portfolio 1(2).

The studentized test statistic d has the form:

$$d = \frac{|\hat{\Delta}|}{s(\hat{\Delta})} \tag{14}$$

where $\hat{\Delta}$ is the estimated difference computed from the original data and $s(\hat{\Delta})$ is a standard error for Δ. Whether these two portfolios have the same Sharpe ratios is equivalent to a two-sided test for $H_0 : \Delta = 0$. Such a test at significance level α can be implemented by constructing a bootstrap confidence interval with confidence level $1-\alpha$. The null hypothesis is rejected if zero is not contained in the interval.

4 Data and Empirical Results

4.1 Data

To study the effects of adding EUA futures contracts to an already diversified portfolio we consider the following standard asset classes: equities, government and corporate bonds, oil, gas and non-energy commodities. The list below contains details of indexes we use to proxy each asset class.

- Phase 1 EUA Futures - EUA Futures front contracts (December 2005 contracts are used to represent Phase 1 EUA Futures prices in 2005, December 2006 contracts are used in 2006, etc.; switch takes place in last trading day of December of each year)
- Phase 2 EUA Futures - December 2008 through to December 2012 EUA Futures Contracts (switch takes place in the last trading day in December of each year)
- Phase 3 EUA Futures - December 2013 through to December 2015 EUA Futures Contracts (switch takes place in the last trading day in December of each year)
- Stocks - Dow Jones Euro Stoxx 50 Index
- Government Bonds - IBOXX Euro Sovereign All Maturities Price Index Corporate Bonds - IBOXX Euro Corporate AAA Rated All Maturities Price Index

- Crude Oil - Dow Jones UBS Energy (DJAIGEN) Sub-Index
- Natural Gas - Dow Jones UBS Energy (DJAIGEN) Sub-Index
- Non-Energy Commodities - Dow Jones UBS Ex. Enery (DJAIGXE) Sub-Index
- Risk-Free Asset - Euribor 1 Month rate

The EUA futures prices are quoted in Euro. EUA futures prices have been obtained from the Intercontinental Exchange (ICE) and the European Climate Exchange (ECX). All other price series have been sourced from Bloomberg. The sample dataset for analyzing Phase 1 EUA futures contains daily price series and covers the period from April 22^{nd} 2005 until December 17^{th} 2007. The dataset for analyzing Phase 2 EUA futures contains daily prices running from January 2^{nd} 2008 until December 17^{th} 2012. The dataset for analyzing Phase 3 EUA futures contains daily prices from start of January 3^{rd} 2013 to July 1^{st} 2015. Besides having similar time series properties to other asset prices in our sample, the EUAs also behave in a similar fashion following the start of the significant economic and stock market downturn in the summer of 2008.[11] This is particularly the case for Phase 2 EUA observations.[12]

Panel A of table 1 contains summary statistics for the Phase 1 dataset. As can be seen, EUA futures delivered a negative annual return of -94% and have by far the highest annual standard deviation of 170.11% compared to all other assets under consideration. The high volatility can be explained by the sharp falls in the EUA futures prices due to overallocation of allowances in the beginning of Phase 1. The negative return is not surprising and can be attributed to the no banking rule between Phase 1 and Phase 2 of the EU ETS. The only two assets with the positive Sharpe ratios are stocks and non-energy related commodities.

[11] We treat each of the Phases separately, as important regulatory and policy differences exist in each case. Our approach of separately examining the Phases is consistent with studies in the literature, e.g. Bredin and Muckley (2011). In Phase 1 (2005-2007), the pilot phase, practically all allowances were allocated freely via grandfathering. Banking of allowances across years was not allowed between Phase 1 and 2. Phase 2 introduced unlimited banking, as well auctioning. This policy effectively places a seam between Phase 1 and 2. Phase 3 (2013-2020) has introduced further flexibility, with 40% of total allowances planned to be auctioned.

[12] A number of specific EU ETS events occurred during Phase 1. In April 2006, coincident to the unofficial release of the 2005 emissions data by some of the EU member states the price of EUAs collapsed. EU ETS prices had reached a high in April 2006. Following the official release by the EU commission on the 15^{th} May 2006, showing a larger than expected surplus in the market, the price fell 50% by mid May 2006. Given that banking EUAs was prohibited between phases, the price eventually converged to close to zero at the end of Phase 1.

Unsurprisingly, government and corporate bonds have the lowest volatility. Natural gas futures had the second worst return after EUA futures and the second highest volatility. Note that return distributions of all assets in this dataset are non-normal as indicated by the Jarque-Bera test statistics - with only two exceptions, oil and government bonds. Taken together the summary statistics for Phase 1 dataset indicates the unattractive nature of EUA futures contracts on an individual basis. Although, as Mansanet-Bataller and Pardo (2008) point out, investors who took short positions in this asset assumed high risk but obtained positive return.

[Please insert table 1 here.]

Panel B of table 1 contains summary statistics for the dataset we use to analyze portfolio performance in Phase 2. Compared to Phase 1, EUA futures in Phase 2 were less volatile with standard deviation of 43.04%, although returns remained in negative territory, -22.55%. Natural gas has the worst return and the highest volatility. Return distributions of all assets in Phase 2 are non-normal as confirmed by the significant Jarque-Bera test statistics. Although Phase 2 EUA futures are highly volatile, they are no longer the worst performing asset class. Compared to Phase 1, the return volatility of Phase 2 EUA futures has reduced significantly from 170.11% to 43.04%.

Turning to Phase 3, panel C of table 1 shows that EUA futures returns remained highly volatile - with the highest standard deviation at 65.41%, of the asset classes examined. That said, EUA futures returns are, during our sample of Phase 3, in positive territory. This could make Phase 3 EUA futures attractive to investors who are risk takers, even without the option of short trades. Other notable summary statistics in Phase 3 include a reversion positive stock returns, after the global financial crisis. Oil and natural gas continue to exhibit negative returns and high volatility. Once again, all asset classes exhibit significant Jarque-Bera test statistics.

Panel A of table 2 reports correlation coefficients for all assets in Phase 1. The EUA futures have positive, though quite low, statistically significant correlations with crude oil and corporate bonds. Correlations with other asset returns are even closer to zero and not statistically significant. Stocks are positively correlated with non-energy commodities and negatively correlated with fixed income securities. All commodities, including crude oil, natural gas and non-energy commodity futures are positively correlated. It is not surprising to note that government and corporate bond indexes are highly correlated.

[Please insert table 2 here.]

Phase 2 correlations are reported in Panel B of table 2. The EUA futures have positive and statistically significant correlations with stocks, crude oil and non-energy commodity futures. Correlations with both government and corporate bonds are negative and statistically significant. Again, all commodities, including crude oil, natural gas and non-energy commodity futures are positively correlated. Non-energy commodity futures are negatively correlated with both corporate and government bonds. As was the case in Phase 1, government and corporate bond indexes are highly correlated, although not to the same extent as in Phase 1. The change in EUAs correlations between Phase 1 and Phase 2 samples is quite dramatic and would point towards the development of these instruments as asset classes. This is particularly the case, given the other asset correlations in the portfolio have not changed dramatically between Phase 1 and 2. Taking account of the *prima facie* diversification potential evidence in Phase 2, there would appear to be a reduction in scope in relation to stock, oil and non energy commodities (significant positive correlations) and some nascent scope relative to government and corporate bonds (significant negative correlations).

Panel C of the table reports no significant correlations between EUA futures and other asset classes in Phase 3. This is indicative of a new emerging independence of EUA futures. It shows *prima facie* evidence of scope for diversification potential, at least relative to stock, oil and non energy commodities, in Phase 3 relative to Phase 2. Additionally, however, the apparent scope for portfolio diversification relative to government and corporate bonds in Phase 2 has diminished significantly in Phase 3.

4.2 Empirical Results

In this section optimal allocations are analyzed for extended minimum variance standard and tangency portfolios. Formal performance comparisons of standard and extended portfolios are conducted using the Jobson-Korkie test and the Ledoit-Wolf robust bootstrap test. For each portfolio type the main performance characteristics such as return, risk and the Sharpe ratio are reported. In addition, the Jarque-Bera normality test are presented for each portfolio type.

Panel A of table 3 shows descriptive statistics in Phase 1 for the returns of extended portfolios constructed using seven different portfolio optimization strategies as outlined in section 3. The classical tangency portfolio is the only one that has a positive return. In terms of risk adjusted excess returns as illustrated by Sharpe ratios, the tangency portfolio does not provide any benefits. All other portfolios do not outperform the risk-free asset and have negative Sharpe ratios. The naive portfolio has the lowest return and the highest volatility. Return distributions of all portfolio types have significant higher moments according to the Jarque Bera test statistic. The hypothesis of return distribution normality is rejected at the 1% significance level. Panel B of table 3 reports the portfolio statistics for the case where short selling of assets is allowed. Extended portfolios TP, TP-BS, TP-LW and TP-BS-LW report large positive Sharpe ratios.

[Please insert table 3 here.]

Panel C of table 3 reports result for the Jobson-Korkie test and the Ledoit-Wolf robust bootstrap test, evaluating the performance of extending the standard portfolios. For example, the Jobson-Korkie test statistic, comparing the performance of the extended minimum variance portfolio and the standard minimum variance portfolio, is -1.40. The test statistic is not statistically significant and so indicates that that extended portfolio does not result in a performance improvement or disimprovement, relative to the standard minimum variance portfolio. Indeed, in the no short-selling case of Panel C, there is no statistically significant difference in the performance of the extended portfolios relative to their standard counterparts across the range of 7 portfolio optimization strategies adopted. In contrast where short selling is allowed, portfolios TP-LW and TP-BS-LW report significant improvements in performance. Therefore, in Phase 1, when short selling is allowed, we confirm, using tangency portfolios: sample mean and Ledoit-Wolf covariance shrinkage estimator (TP-LW) or the Bayes-Stein mean shrinkage estimator and Ledoit-Wolf covariance shrinkage estimator (TP-BS-LW), that the inclusion of carbon in the portfolio can contribute significantly to improved performance.[13] [14]

Panel A of table 4 contains descriptive statistics for the returns of extended portfolios

[13]It is also noteworthy that TP-BS shows improved performance when carbon is included using the Ledoit-Wolf robust bootstrap test, albeit not with the Jobson-Korkie test.

[14]The corresponding time-varying (a 6-month rolling window) portfolio allocations, switch substantively across the no short selling and short selling environments. There is a negative weight on EUA futures throughout the majority of the time in Phase 1 in respect to TP, TP-BS, TP-LW and TP-BS-LW. Plots of the portfolio allocations are available from the authors upon request.

in Phase 2 when short-selling is not allowed. All portfolios have negative Sharpe ratios. The Jobson-Korkie test and the Ledoit-Wolf robust bootstrap test are reported in Panel C of the table. Both measures of portfolio performance are perfectly consistent and indicate that there is no performance benefit from augmenting the Phase 2 standard portfolios with EUA futures. This result is consistent with the no-short selling environment using the Phase 1 sample. Panel B of table 4 contains descriptive statistics for the returns of extended portfolios in Phase 2 when short selling is permitted. Unlike Phase 1, allowing short-selling does not result in high returns for the extended portfolios. When comparing extended and standard portfolios, with the same optimization strategy, the Jobson-Korkie test and the Ledoit-Wolf robust bootstrap test, both indicate no performance improvement.

[Please insert table 4 here.]

Panel A (B) of table 5 contains descriptive statistics for the returns of extended portfolios in Phase 3 when short-selling is not (short-selling is) allowed. The extended tangency portfolios exhibit negative Sharpe ratios in both the short selling and no short selling imposed environments. The Jobson-Korkie test and the Ledoit-Wolf robust bootstrap test are reported in Panel C of the table. These test results are also consistent with findings in Phase 2. There is no significant improvement (or dis-improvement) in the performance of standard portfolios, due to the inclusion of EUA futures.

[Please insert table 5 here.]

The Phase 2 and 3 short sales and no-short sales findings are consistent. The portfolio benefits from augmenting the portfolio with EUAs arises in particular during Phase 1, when there was a predictable fall in the price, as a result of the over supply of emission rights and the no banking rule between Phase 1 and 2. The benefits to portfolio optimization become clear once short selling is permitted. However, for Phase 2 and beyond, the no-banking rule has been abandoned and there is no evidence of clear portfolio augmentation benefits.

5 Mean Variance Spanning

In Table 6 we test whether the minimum variance frontier of benchmark assets alters as a result of including a new risky asset, EUA futures (a test asset). We permit short sales and we focus exclusively on the sample mean and the sample covariance matrix. As in our prior analyses, our tests are conducted in Phase 1, Phase 2 and Phase 3 of the EU ETS. We present results for the asymptotic likelihood ratio spanning test (Huberman and Kandel, 1987) and the corrected F-test, Wald tests robust to certain non-normalities in returns and step down tests (Kan and Zhou, 2012).

[Please insert table 6 here.]

In Panel A of table 6, the likelihood ratio test statistic rejects the null hypothesis at the 1% level in Phase 1, and at the 5% level in Phase 3, and it does not reject the null hypothesis at any level in Phase 2.[15] Furthermore, the corrected F-test and Wald test statistics, the latter robust to certain non-normalities in returns, indicate consistent results. Hence, the standard benchmark portfolio of assets do not span the test asset in Phase 1 or in Phase 3 but they do span the test asset in Phase 2. Our results indicate that EUA futures statistically improve the investment opportunity set of benchmark assets in Phase 1 and 3, but not Phase 2. We cannot, however, necessarily attribute the statistical power of this test to economic significance in terms of portfolio diversification benefits. It may turn out the rejection of the null hypothesis stems from the statistical power of the likelihood ratio test (and Wald tests) but does not align well with the economic significance of the difference between the extended and standard minimum variance frontiers.[16]

When testing for differences in minimum variance frontiers it is natural statistically to put more weight on relatively accurately estimated portfolios, e.g., the global minimum variance portfolio, however a small difference in the global minimum variance portfolio which may be statistically significant may not align well with economic significance.[17] In addition, when there is a risk free rate instrument available in the market then mean-variance investors will be exclusively interested in the tangency portfolio (the portfolio that maximises the Sharpe ratio). To the extent that investors are not inclined to hold the global minimum variance portfolio (this would imply that a unique risk free rate was

[15] Kan and Zhou, 2012, also provide Wald and Lagrange multiplier tests for the same null hypothesis. These tests, however, in our setting of a single test asset, are straightforward transformations of the adopted likelihood ratio test and thus are equivalent tests in general. As a result, these tests are perfect substitutes as they are equally powerful in a statistical sense.

[16] These tests have strong power to reject the spanning hypothesis for a test asset that can improve the variance of the global minimum-variance portfolio but little power for a test asset that can improve the tangency portfolio (Kan and Zhou, 2012).

[17] Furthermore, a big difference in the tangency portfolio may be difficult to detect statistically but may be of great economic importance. The sampling error of the minimum variance portfolio is likely to be much less than that of the tangency portfolio, as its estimation does not require an estimate of the expected return and thus it is more accurately estimated.

not available in the market) there is no economic motivation to test for alterations in the minimum variance portfolio due to the inclusion of EUA futures.

To take account of the problems highlighted above, in panel B of table 6 we present additional step-down spanning test results. The null hypothesis that the benchmark assets span the test assets can be disaggregated into two joint tests (so-called step-down spanning tests). First, a test of whether the new tangency portfolio has a zero weight in the EUA futures (F1 in panel B of table 6) and second a test of whether the minimum variance portfolio has a zero weight in the EUA futures (F2 in panel B of table 6). We find evidence that in Phase 1 and Phase 3, the minimum variance frontier is improved due to the inclusion of EUA futures. This improvement in the investment opportunity set arises due to not only an improvement in the minimum variance portfolio but importantly from an economic viewpoint, an improvement in the tangency portfolio. However, the improvement in the tangency portfolio only takes place in Phase 1.

Our results indicate that there is considerable portfolio diversification benefits during Phase 1 and not in Phase 2 or in Phase 3. This finding is consistent with the nature of a emerging asset during the Pilot Phase and also the general indication of a move by fund managers into this market.[18] In particular, we only see the portfolio improvement in Phase 1 for the case of short-selling, while in Phase 2 or 3 there are no portfolio improvements for the case of either short-sales or no short sales regulatory environments. Previous empirical evidence, see Bredin and Muckley (2011), Bredin *et al.* (2014), Bredin and Parsons (2016) and Chen *et al.* (2017) has indicated considerable market development of the EU ETS during Phase 2. Our finding of portfolio benefits during the Pilot Phase and not during the Kyoto Phase, or thus far in Phase 3, is consistent with these studies.

6 Conclusions

The rapid growth of a European emissions trading market has led to the establishment of emission allowances as a new financial asset. The new market has attracted new participants, such as hedge funds, pension funds, foundations, and other plan sponsors. These investors have no emission reduction obligations and participate in the carbon markets in

[18]Recent evidence presented by Ibikunle and Sheffen (2015) has found that European green mutual funds have underperformed conventional mutual funds over the 1991-2014 period.

order to extend their investment opportunities through diversification (Lucia, Mansanat-Bataller and Pardo, 2015). As has been highlighted by Bredin and Muckley (2011), there is new evidence of equilibrium drivers of carbon prices in Europe which follows, at least in the long-term after Phase 1, key macroeconomic and energy variables.

The emerging nature of this new asset class is also evident when examined from the portfolio perspective. Our analysis covers the complete history of the EU ETS Phase 1, 2 and 3, rather than the predominantly pilot based focus of the previous studies. Formal tests are performed to compare portfolio performance using the Jobson-Korkie (1980) test and the robust bootstrapping method of Ledoit-Wolf (2004b). We also conduct a series of sensitivity analysis using mean variance spanning tests (Huberman and Kandel, 1987 and Kan and Zhou, 2012). We find consistent evidence of portfolio diversification benefits from carbon, however only for short-sales and only for Phase 1. During Phase 2 in which the market matured quite considerably (see Bredin *et al.*., (2014) and Chen *et al.* (2017)), we find no evidence of portfolio diversification benefits.

Our results are consistent with the narrative of extensive risk capital being attracted to carbon markets in particular during Phase 1 of the EU ETS. During the first stage of the ETS, a large number of US and European hedge funds and private equity funds were attracted to the market and invested in carbon credits or alternatively via equity stakes in carbon firms (see, Labatt and White, 2007). Our results can reflect the maturing nature of the carbon market in Europe and establishment of an asset class driven by fundamentals.

References

[1] Afonin, A., Bredin, D., Muckley, C. (2012), "'Carbon credits and portfolio management"', *Energy and Value Letter* 4, 10-22.

[2] Amin, G. Kat, H. (2003), "Stocks, bonds and hedge funds: Not a free lunch.", *The Journal of Portfolio Management*, 113-120.

[3] Börger, R., Cartea, A., Kiesel, R., Schindlmayr, G. (2009), "'Cross-commodity analysis and applications to risk management"', *The Journal of Futures Market* 29, 197-217.

[4] Bredin, D., Muckley, C., (2011), "An Emerging Equilibrium in the EU Emissions Trading Scheme", *Energy Economics*, 33, 353-362.

[5] Bredin, D., Hyde, S., Muckley, C. (2014), "A Microstructure Analysis of the Carbon Finance Market", *International Review of Financial Analysis*, 34, 222-234.

[6] Bredin, D., Parsons, J., (2016) "Why is Spot Carbon so Cheap and Future Carbon so Dear? The Term Structure of Carbon Prices", *Energy Journal*, 37, 83-107.

[7] Chen, J., Muckley, C., Bredin, D. (2017), "Is information assimilated at announcements in the European Carbon Market?", *Energy Economics*, 63, 234-247.

[8] Chevallier, J., (2009), "Energy risk management with carbon assets", *International Journal of Global Energy Issues*, 32, 328-349.

[9] DeMiguel, V., Garlappi, L., Uppal, R. (2009), "Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy?", *Review of Financial Studies*, 22, 1915-1953.

[10] DeMiguel, V., Garlappi, L., Nogales, F.J., Uppal, R. (2009a), "A Generalized Approach to Portfolio Optimization: Improving Performance by Constraining Portfolio Norms", *Management Science*, 55, 798-812.

[11] DeMiguel, V., Garlappi, L., Uppal, R. Vilkov, G. (2013), "Improving Portfolio Selection Using Option-Implied Volatility and Skewness.", *Journal of Financial and Quantitative Analysis*, 48(6), 1813-1845.

[12] Ellerman, D., Marcantonini, C., Zaklan, A., 2014. The EU ETS: Eight Years and Counting, Robert Schuman Centre for Advanced Studies, Climate Policy Research Unit, RCAS 2014/14.

[13] Erb, G., Harvey, C. (2006), "The strategic and tactical value of commodity futures", *Financial Analysis Journal*, 62, 69-97.

[14] Fabozzi, F.J., Focardi, S.M., Mercer, J. (2006) *Financial Modeling of the Equity Market: From CAPM to Cointegration*, Wiley, US.

[15] Jensen, G., Johnson, R., Mercer, J. (2000), "Efficient use of commodity futures in diversified portfolios", *Journal of Futures Markets*, 20, 489-506.

[16] Jobson, J., Korkie, B. (1980), "Estimation for Markowitz efficint portfolios", J*ournal of the American Statistical Association*, 75, 544-554.

[17] Jorion, P. (1986), "Bayes-stein estimation for portfolio analysis", *The Journal of Business*, 58, 279-292.

[18] Huberman, G., Kandel, S. (1987), "Mean Variance Spanning", *Journal of Finance*, 42, 873-888.

[19] Kan, R., Zhou, G. (2012), "Tests of Mean Variance Spanning", *Annals of Economics and Finance*, 13-1, 139-187.

[20] Labatt, S., White, R.R. (2007), *Carbon Finance: The Financial Implications of Climat Change*, John Wiley & Sons, New Jersey.

[21] Lucia, J., Mansanet-Bataller, M., and Pardo, A. (2015), *Speculative and hedging activities in the European carbon market*, Energy Policy, 82, 342-351.

[22] Ledoit, O., Wolf, M. (2003), "Improved estimation of the covariance matrix of stock returns with an application to portfolio selection", *Journal of Empirical Finance*, 10, 603-621.

[23] Ledoit, O., Wolf, M. (2004a), "A well-conditioned estimator for large-dimensional covariance matrix", *Journal of Multivariate Analysis*, 88, 365-411.

[24] Ledoit, O., Wolf, M. (2004b), "Honey, I shrunk the sample covariance matrix", *Journal of Portfolio Management*, 30, 4, 110-119.

[25] Ledoit, O., Wolf, M. (2008), "Robust performance hypothesis testing with the sharpe ratio", *Journal of Empirical Finance*, 15, 850-859.

[26] Mansanet-Bataller, M., Pardo, A. (2008), "CO_2 Prices and Portfolio Management", SSRN Working Paper number 1156975.

[27] Mansanet-Bataller, M. (2011), "CO_2 Prices and Portfolio Management during Phase II of the EU ETS", Climate Economics Chair Publications, Working Paper Series Number 01.

[28] Markowitz, H. (1952), "Portfolio selection", *The Journal of Finance*, 7, 77-91.

[29] Memmel, C. (2003), "Performance Hypothesis Testing with the Sharpe Ratio", *Finance Letters*, 1, 21-23.

[30] Michaud, R. (1989), "The Markowitz optimization enigma: Is optimized optimal?", *Journal of Financial and Quantitative Analysis*, 21, 31-42.

[31] Michaud, R. (1998), "*Efficient asset management: A practical guide to stock portfolio optimization and asset allocation*". *Oxford University Press.*

[32] Reboredo, JC, Ugando, M. (2015), "'Downside risks in EU carbon and fossil fuel markets"', *Mathematics and Computers in Simulation* 111, 17-35.

[33] Reboredo, JC. (2013), "'Modelling EU allowances and oil market interdependence. Implications for portfolio management"', *Energy Economics* 36, 471-480.

7 Tables

Table 1: Summary Statistics

	Mean (%)	Std Dev (%)	Sharpe	JB Stats
Panel A: Phase 1				
EUA	-94.00	170.11	-0.57	149363.82**
Stocks	14.98	14.53	0.81	38.63**
Oil	0.29	27.86	-0.10	3.90
NG	-40.49	49.53	-0.88	118.51*
NE Comm.	8.70	14.50	0.38	33.17**
Gov Bonds	-2.60	3.08	-1.86	0.12
Corp Bonds	-2.72	1.89	-3.10	8.54**
Panel B: Phase 2				
EUA	-22.55	43.04	-0.56	628.63**
Stocks	-9.63	29.07	-0.38	828.9**
Oil	-15.47	36.35	-0.47	559.63**
NG	-41.47	44.57	-0.96	52.76**
NE Comm.	3.90	18.09	0.14	133.24**
Gov Bonds	1.52	4.43	0.01	313.36**
Corp Bonds	1.81	4.50	0.08	9201.97**
Panel C: Phase 3				
EUA	6.61	65.41	0.10	13212.21**
Stocks	10.98	17.45	0.62	46.18**
Oil	-13.58	27.67	-0.49	754.95**
NG	-8.54	38.29	-0.23	65.62**
NE Comm.	-5.21	11.80	-0.45	43.1**
Gov Bonds	2.21	3.38	0.62	528.8**
Corp Bonds	1.47	3.36	0.41	134.76**

Note:
*(**) represents significance at the 5%(1%) level.

Table 2: Correlations

	EUA	Stocks	Oil	NG	NE Comm.	Gov Bonds
Panel A: Phase 1						
Stocks	-0.01					
Oil	0.10**	0.09*				
NG	0.06	0.02	0.43**			
NE Comm.	0.05	0.29**	0.37**	0.16**		
Gov Bonds	0.05	-0.25**	-0.05	0.04	-0.16**	
Corp Bonds	0.08*	-0.30**	-0.04	0.04	-0.16**	0.95**
Panel B: Phase 2						
Stocks	0.27**					
Crude Oil	0.23**	0.38**				
Natural Gas	0.04	0.02	0.23**			
Non-Energy Commod.	0.14**	0.29**	0.55**	0.22**		
Government Bonds	-0.08**	-0.19**	-0.2**	-0.03	-0.13**	
Corporate Bonds	-0.13**	-0.37**	-0.21**	0.04	-0.06**	0.52**
Panel C: Phase 3						
Stocks	0.04					
Oil	0.05	0.12**				
NG	0.03	0.04	0.12**			
NE Comm.	-0.01	0.15**	0.25**	0.08**		
Gov Bonds	-0.05	0.18**	-0.01	0.01	0.19**	
Corp Bonds	-0.07	-0.14**	-0.05	-0.03	0.13**	0.74**

Note:
*(**) represents significance at the 5%(1%) level.

.

Table 3: Optimal Extended and Standard Portfolio Statistics in Phase 1

	Panel I: Extended Portfolio				Panel II: Standard Portfolio			
	Mean (%)	Std Dev (%)	Sharpe	JB Stats	Mean (%)	Std Dev (%)	Sharpe	JB Stats
Panel A No Short-Selling								
GMV	-2.16	1.73	-0.20	8.62*	-2.15	1.73	-0.20	8.67*
GMV-LW	-1.61	3.99	-0.08	260.99**	-1.04	2.25	-0.12	8.56*
TP	2.16	16.96	0.00	239.86**	4.39	15.69	0.00	7.60*
TP-BS	-2.72	21.36	-0.02	775.49**	-1.71	19.56	-0.02	35.79**
TP-LW	-1.34	18.47	-0.02	557.30**	2.50	16.26	0.00	9.80*
TP-BS-LW	-6.17	23.15	-0.03	1251.36**	-3.60	20.41	-0.02	67.07**
NP	-42.75	27.70	-1.67	42252.38**	-12.21	12.05	-0.09	6.16*
Panel B Short-Selling Allowed								
GMV	-2.47	1.27	-4.62	622.97**	-2.37	1.26	-4.59	619.21**
GMV-LW	-1.22	4.02	-1.15	253.28**	-0.86	2.25	-1.89	9.11*
TP	362.29	101.72	3.53	10742.17**	24.41	52.55	0.40	23.04**
TP-BS	477.13	112.75	4.20	10706.57**	16.57	66.22	0.20	35.04**
TP-LW	652.44	119.01	5.45	13088.89**	13.01	59.07	0.16	19.69**
TP-BS-LW	805.75	129.02	6.22	16958.66**	16.35	69.29	0.19	47.88**
NP	-42.75	27.70	-1.67	42252.39**	-12.21	12.05	-1.29	6.16*

Table 3-Continued: Optimal Extended and Standard Portfolio Statistics in Phase 1

	No Short-Selling		Short-Selling Allowed	
	JK Test	LW Test	JK Test	LW Test
Panel C JK LW Test Results				
GMV	-1.40	0.98	-0.49	0.43
GMV-LW	1.44	1.47	1.47	1.51
TP	-0.42	0.44	1.50	1.78
TP-BS	-0.07	0.08	1.83	2.20*
TP-LW	-0.57	0.61	2.01*	2.42*
TP-BS-LW	-0.19	0.21	1.98*	2.37*
NP	-1.07	1.21	-1.07	1.21

Note:
GMV refers to the Global Minimum Variance Portfolio based on sample covariance matrix. GMV-LW refers to the Global Minimum Variance Portfolio using Ledoit-Wolf covariance shrinkage estimator. TP refers to the Tangency Portfolio based on sample mean and sample covariance matrix. TP-BS refers to the Tangency Portfolio estimated using Bayes-Stein mean shrinkage estimator and sample covariance matrix. TP-LW refers to the Tangency Portfolio estimated using sample mean and Ledoit-Wolf covariance shrinkage estimator. TP-BS-LW refers to the Tangency Portfolio based on Bayes-Stein mean shrinkage estimator and Ledoit-Wolf covariance shrinkage estimator. Finally, NP refers to the Naive Portfolio that uses the same allocation for all assets. Panel C reports results of the Jobson-Korie as well as the Ledoit-Wolf bootstrap studentized test statistic comparing Sharpe ratios of extended and standard optimal portfolio strategies for various optimal portfolios in Phase 1. *(**) represents significance at the 5%(1%) level.

Table 4: Optimal Extended and Standard Portfolio Statistics in Phase 2

	Panel I: Extended Portfolio				Panel II: Standard Portfolio			
	Mean (%)	Std Dev (%)	Sharpe	JB Stats	Mean (%)	Std Dev (%)	Sharpe	JB Stats
Panel A No Short-Selling								
GMV	-0.42	3.62	-0.44	1775.36**	-1.61	4.19	-0.66	16335.29**
GMV-LW	-0.82	3.97	-0.50	688.45**	0.30	3.76	-0.23	903.2**
TP	-14.58	16.22	-0.97	16517.58**	16.48	38.08	0.40	1219.79**
TP-BS	-14.51	17.74	-0.88	13720.95**	7.61	44.57	0.14	1637.73**
TP-LW	-14.38	17.22	-0.90	11417.49**	31.68	46.14	0.66	403.55**
TP-BS-LW	-14.75	18.15	-0.88	11428.33**	10.73	49.82	0.19	912.75**
NP	-14.92	15.08	-1.07	137.9**	-13.28	14.50	-1.00	145.1**
Panel B Short-Selling Allowed								
GMV	-2.02	4.20	-0.76	15825.59**	-3.79	3.62	-1.70	61072.16**
GMV-LW	-0.63	3.99	-0.45	664.23**	-1.65	3.49	-1.16	13083.24**
TP	7.95	42.97	0.16	1126.97**	13.25	47.63	0.23	407.9**
TP-BS	-6.96	59.52	-0.14	8979.45**	36.28	64.37	0.53	1116.2**
TP-LW	9.82	57.16	0.15	447.7**	17.71	55.89	0.27	165.37**
TP-BS-LW	-5.18	66.63	-0.10	4504.86**	39.32	68.68	0.54	1120.24**
NP	-14.92	15.08	-1.07	137.9**	-12.80	14.23	-1.07	277.74**

Table 4-Continued: Optimal Extended and Standard Portfolio Statistics in Phase 2

	No Short-Selling		Short-Selling Allowed	
	JK Test	LW Test	JK Test	LW Test
Panel C JK LW Test Results				
GMV	-1.46	1.16	-1.39	1.11
GMV-LW	-1.61	1.43	-1.6	1.42
TP	0.13	0.13	-0.84	0.77
TP-BS	0.11	0.11	-0.7	0.68
TP-LW	0.11	0.11	-1.4	1.31
TP-BS-LW	0.09	0.09	-0.76	0.72
NP	-0.43	0.40	-0.43	0.40

Note:
GMV refers to the Global Minimum Variance Portfolio based on sample covariance matrix. GMV-LW refers to the Global Minimum Variance Portfolio using Ledoit-Wolf covariance shrinkage estimator. TP refers to the Tangency Portfolio based on sample mean and sample covariance matrix. TP-BS refers to the Tangency Portfolio estimated using Bayes-Stein mean shrinkage estimator and sample covariance matrix. TP-LW refers to the Tangency Portfolio estimated using sample mean and Ledoit-Wolf covariance shrinkage estimator. TP-BS-LW refers to the Tangency Portfolio based on Bayes-Stein mean shrinkage estimator and Ledoit-Wolf covariance shrinkage estimator. Finally, NP refers to the Naive Portfolio that uses the same allocation for all assets. Panel C reports results of the Jobson-Korie as well as the Ledoit-Wolf bootstrap studentized test statistic comparing Sharpe ratios of extended and standard optimal portfolio strategies for various optimal portfolios in Phase 2. *(**) represents significance at the 5%(1%) level.

Table 5: Optimal Extended and Standard Portfolio Statistics in Phase 3

	Panel I: Extended Portfolio				Panel II: Standard Portfolio			
	Mean (%)	Std Dev (%)	Sharpe	JB Stats	Mean (%)	Std Dev (%)	Sharpe	JB Stats
Panel A No Short-Selling								
GMV	3.54	2.96	1.16	46.69**	3.39	2.99	1.10	47.58**
GMV-LW	2.76	3.79	0.70	1.44	3.37	3.13	1.04	34.69**
TP	-0.26	9.14	-0.04	450.88**	-0.29	9.15	-0.04	516.63**
TP-BS	-0.26	9.00	-0.04	596.34**	-0.32	9.08	-0.05	637.28**
TP-LW	-1.15	10.20	-0.12	169.44**	-0.17	9.83	-0.03	269.73**
TP-BS-LW	-0.13	9.79	-0.02	200.55**	0.10	9.54	0.00	375.64**
NP	2.97	11.02	0.26	25.28**	-1.59	10.07	-0.17	38.97**
Panel B Short-Selling Allowed								
GMV	3.54	2.97	1.16	48.3**	3.38	3.00	1.09	48.91**
GMV-LW	2.76	3.79	0.70	1.44	3.37	3.13	1.04	34.69**
TP	-2.10	12.44	-0.18	6678.07**	-1.87	12.21	-0.16	7267.14**
TP-BS	-8.92	24.19	-0.37	37869.67**	-8.87	24.25	-0.37	38813.01**
TP-LW	-11.18	26.86	-0.42	5422.2**	-3.24	16.99	-0.20	3846.69**
TP-BS-LW	-12.73	26.46	-0.49	6728.75**	-10.42	25.79	-0.41	20484.47**
NP	2.97	11.02	0.26	25.28**	-1.59	10.07	-0.17	38.97**

Table 5-Continued: Optimal Extended and Standard Portfolio Statistics in Phase 3

	No Short-Selling		Short-Selling Allowed	
	JK Test	LW Test	JK Test	LW Test
Panel C				
JK LW Test Results				
GMV	0.81	0.90	0.86	0.97
GMV-LW	-0.78	0.78	-0.78	0.78
TP	0.02	0.02	-0.11	0.12
TP-BS	0.06	0.06	-0.05	0.06
TP-LW	-0.28	0.29	-0.72	0.76
TP-BS-LW	-0.08	0.09	-0.28	0.30
NP	0.95	1.01	0.95	1.01

Note:
GMV refers to the Global Minimum Variance Portfolio based on sample covariance matrix. GMV-LW refers to the Global Minimum Variance Portfolio using Ledoit-Wolf covariance shrinkage estimator. TP refers to the Tangency Portfolio based on sample mean and sample covariance matrix. TP-BS refers to the Tangency Portfolio estimated using Bayes-Stein mean shrinkage estimator and sample covariance matrix. TP-LW refers to the Tangency Portfolio estimated using sample mean and Ledoit-Wolf covariance shrinkage estimator. TP-BS-LW refers to the Tangency Portfolio based on Bayes-Stein mean shrinkage estimator and Ledoit-Wolf covariance shrinkage estimator. Finally, NP refers to the Naive Portfolio that uses the same allocation for all assets. Panel C reports results of the Jobson-Korie as well as the Ledoit-Wolf bootstrap studentized test statistic comparing Sharpe ratios of extended and standard optimal portfolio strategies for various optimal portfolios in Phase 3. *(**) represents significance at the 5%(1%) level.

Table 6: Spanning Test and Step-down Test Results

	Phase 1 EUA Futures	Phase 2 EUA Futures	Phase 3 EUA Futures
Panel A: Multivariate Spanning Tests			
Likelihood Ratio	12.74**	5.62	6.1*
Wald	12.86**	5.63	6.13*
Panel B: Step-Down Tests			
Joint corrected F Test	6.36**	2.80	3.03*
F1 Test	5.42*	1.04	0.04
F2 Test	7.26**	4.55*	6.03*

Note:
In Panel A of the table, we report results of the Huberman and Kandel (1987) multivariate spanning likelihood ratio test, as well as the Kan and Zhou (2012) asymptotic Wald spanning tests (which are robust to conditional heteroskedasticity and assume the i.i.d. elliptical distribution assumption) and corrected F-test. In Panel C of the table, the step-down tests of Kan and Zhou (2012) are reported in respect to EUA Phase 2 and 3 futures. *(**) represents significance at the 5%(1%) level.