Does the Early Exercise Premium Contain Information about Future Underlying Returns?*

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First Draft: August 2003
This Draft: August 2005

*We thank Michael Brennan, Richard Roll, Avanidhar Subrahmanyam, and Bob Whaley for very helpful and detailed comments, and Peter Carr, Louis Ederington, Robert Geske, Eric Ghysels, Francis Longstaff, Alberto Plazzi, Alessio Saretto, and Sergei Sarkissian for useful suggestions. We are grateful to Jason Hsu for providing the FTSE futures data. All remaining errors are our own responsability.

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Abstract

We investigate the information content of the call (put) Early Exercise Premium, or *EEP*, defined as the normalized difference in prices between otherwise comparable American and European call (put) options. The call *EEP* specifically captures investors' expectations about future lump sum dividend payments as well as other state variables such as conditional volatility and interest rates. From that perspective, the *EEP* should also be related to future returns of the underlying security. Little is known about the *EEP*, largely because it is usually unobservable for most underlying securities. The FTSE 100 index is an exception in that regard, because it has both American and European options contracts that are traded in large volumes. We use data of the FTSE 100 index, and its American and European options contracts, from which we compute a time series of the *EEP*. Interestingly, we find that the *EEP* is a good forecaster of returns at daily horizons. This forecastability is not due to time-variation in market risk premia or liquidity. Importantly, we find that the predictability stems primarily from the ability of the *EEP* to forecast innovations in dividend growth, rather than other components of unexpected returns. Overall, we use several empirical and simulation methods to establish predictability of the underlying with an options market variable, link this predictability to information about cash flow fundamentals, and thereby provide clear support for Black's (1975) conjecture that informed investors prefer to trade on their superior information about fundamentals in the options market relative to the underlying.

1 Introduction

Black (1975) was one of the first to suggest that informed investors prefer to trade on their superior information about fundamentals in the options market rather than in the underlying asset market because they can easily take on more leveraged positions. An important implication of this argument is that, over short horizons, option prices will reflect news about fundamentals that is yet to be incorporated into prices of the underlying security. Since the transmission of information across markets, and particularly between the options and the underlying market, is of central importance in finance, it is not surprising that this conjecture has generated a lot of theoretical and empirical interest. On the theoretical side, Biais and Hillion (1994), Easley, O'Hara, and Srinivas (1998) and others elaborate and formalize the theoretical conditions under which Black's (1975) conjecture will hold.

Unfortunately, the empirical literature on this topic has yet to reach a consensus. The debates revolve around two related points. First, from an empirical perspective, to what extent do option prices as well as other information in the option market predict movements in the underlying security? Amin and Lee (1997), Anthony (1988), Chakravarty, Gulen, and Mayhew (2004), and Pan and Poteshman (2004) find that options market variables (such as changes in option prices, implied volatility, and option volume) predict returns of the underlying security at short horizons. In contrast, Stephan and Whaley (1990) and Chan, Chung, and Johnson (1993) fail to find such predictive relations. Second, if predictability is observed, is it due to traders' information about fundamentals? This second point is particularly important in order to establish whether the predictability supports Black's (1975) conjecture or whether it is due to some other deviations from perfect markets.

In this paper, we take an altogether new look at the connection between prices of options and the underlying security, and its link with information about fundamentals. More specifically, we focus on the difference in prices between otherwise comparable European and American call options, which is known as the call early exercise premium, or call EEP.

Merton (1973) was the first to show that the call *EEP* must be zero if the underlying asset pays no dividends.[1] Roll (1977), Geske (1979), and Whaley (1981) prove that in the presence of a known lump sum dividend, prices of European and American calls are not necessarily equal, because American option holders might want to exercise the option right before the ex-dividend date. In the more realistic case of multiple dividends that are not known with certainty, the *EEP* will depend on both the expected magnitude and the lumpiness of these dividends.[2] Conditional on dividends being non-zero, the *EEP* will also depend on other factors that affect option prices (volatility, interest rates, etc.). Therefore, when dividends are non-zero and lumpy, changes in expectations about future cash flows and discount rates of the underlying asset ought to be reflected in a non-zero mean and variations of the early exercise premium.

We focus on the call *EEP* rather than on other option market predictors, because of its close and unambiguous connection with lump sum dividends. The arguments in Roll (1977), Geske (1979), and Whaley (1981) suggest that the call *EEP* is very sensitive to changes in expectations about future lumpy dividends. Furthermore, based on an empirical exercise of S&P 100 index options, Whaley (1982) and Harvey and Whaley (1992a, 1992b) conclude that the magnitude and timing of dividends is critically important in determining the early exercise premium. More specifically, Whaley (1982) remarks that the "magnitude of the early exercise premium is importantly influenced by the amount of the dividend payment." Harvey and Whaley (1992a) provide additional evidence and make this point even more forcefully by concluding that: "From a practical standpoint of pricing (or trading) S&P 100 index options, knowing the amount and timing of S&P 100 index cash dividends appears to be critical." In the context of the FTSE 100 index options, the dependence of dividends

[1]The intuition is that, in the absence of dividends, the intrinsic value obtained from exercising an American call option is always less than the value of the option. An investor would therefore rather sell the option in the open market rather than exercise it early.

[2]When dividends are lumpy and non-uniform, the probability of early exercise is higher, and the magnitude of the early exercise premium is dependent not just on the last dividend before option maturity, but also on the other (lumpy) dividends over the life of the option.

of the *EEP* should be even more important since FTSE 100 index dividends have been clustered once every two weeks, and hence been highly lumpy and non-uniform. In contrast, predictors such as the change in prices of American options, volume, open interest, and even the *put EEP* depend not only on the lumpy dividends but on all the other factors that affect option prices. For simplicity, by "*EEP*" we refer to the call *EEP* unless otherwise specified.

Clearly, analytic arguments and extant empirical findings suggest that the *EEP* is very sensitive to fluctuations about future dividend payments.[3] We conjecture that, to the extent that dividend expectations influence returns and to the extent that Black's (1975) argument holds, the *EEP* should also be a particularly good predictor of underlying returns at short horizons of a few days–horizons that lie within the period that it takes for information to be impounded into underlying prices. In the context of Black (1975), if informed investors trade primarily in the options market, their information will be incorporated first in the markets for European and American options rather than in the market for the underlying. Since dividend information specifically has a different effect on American relative to European options, the EEP should capture dividend information faster than the underlying.[4]

In practice, the *EEP* is rarely directly observable, because virtually all underlying assets have either American or European options, but not both.[5] One notable exception is the FTSE 100 index which has both American and European contracts that are traded in large volumes. Both types of contracts have co-existed on the London International Financial Futures Exchange (LIFFE) exchange from 1990 until the present and have high liquidity, very similar maturity, and other characteristics. This presents us a unique opportunity to directly observe the *EEP* and to revisit the debate about the information flow between the options and the underlying security markets, and, more importantly, to associate the

[3]Even though ex-post dividends tend to be highly persistent, there is a great degree of ex-ante uncertainty about their innovations, and the importance of these is recognized both by academics and practitioners.

[4]The private information that can be differentially incorporated into prices is not necessarily market-wide, but also firm-specific since only a handful of stocks go ex-dividend on any particular ex-dividend date and the dividend expectations that influence the early exercise premium relate to these firm-specific dividends.

[5]The S&P 500 index had both American and European contracts from April 2, 1986 through June 20, 1986.

information flow to information about fundamentals.

In this paper, we investigate the empirical relation between the early exercise premium of call options and the returns of the FTSE 100 index using daily data from June 1992 to January 1996. First, we describe the statistical properties of the early exercise premium. We document that, for calls and puts, the average *EEP* is non-zero and its magnitude is economically and statistically significant. The time series of the *EEP* also exhibits significant serial correlation at horizons up to one week. This finding suggests that the call *EEP* might be related to lumpy dividend payments of the underlying index. We use the Longstaff and Schwartz (2001) simulation approach to show that, indeed, a simple model which calibrates the lumpy sum dividends, the conditional volatility, and the interest rate processes has little trouble to replicate the magnitudes of the average *EEP* and its serial correlation that are found in the data.

Second, we investigate the information content in the *EEP*. We do that by first looking at whether the *EEP* can forecast subsequent FTSE 100 returns. This forecasting relation is motivated by the fact that since FTSE 100 index dividends are paid approximately once every two weeks in lump sums,[6] the call *EEP* ought to contain information, most importantly about future dividend yields, but also about future volatility, and future interest rates, all of which have been used extensively as forecasters of returns (Campbell and Shiller (1988a), Ghysels, Santa-Clara, and Valkanov (2005b), and Campbell (1991)). Hence, since the *EEP* captures fluctuations in these variables, it should arguably be a useful forecaster of FTSE 100 returns. We find that the *EEP* does actually forecast the index returns at one- and two-day horizons. This predictive relation is robust to the addition of other control variables such as dividend yield, short interest rate, implied volatility, and changes in volume. The forecasting relation also persists in subsamples. The forecastability disappears at longer horizons.

The ability of the *EEP* to forecast returns is markedly different from that of the

[6]We will explain the institutional requirements in the data section.

dividend yield, the volatility, and interest rates in two important aspects. From a statistical perspective, the *EEP* contains information about dividend yields, volatility, and interest rates but does not suffer from the well known-statistical problems (such as extreme persistence and low volatility) which have rendered forecasting with these predictors quite problematic (Stambaugh (1999), Ferson, Sarkissian, and Simian (2003), Torous, Valkanov, and Yan (2005)). The autocorrelation of the *EEP*, while significantly different from zero, is not near the boundary of non-stationarity and will not significantly bias the estimates in forecasting regressions. Also, the volatility of the *EEP* is actually larger than that of the FTSE 100 returns. This is in contrast to the volatilities of other predictors, which are at least an order of magnitude lower than that of the returns. These appealing statistical properties of the *EEP* make it a suitable forecaster of returns, especially at short horizons.

From an economic perspective, the source of the *EEP* predictability also differs from that of other widely used conditioning variables. Campbell and Shiller (1988b), Fama and French (1989), Campbell (1991), Ghysels, Santa-Clara, and Valkanov (2005b) and others argue that the dividend yield, volatility, and interest rates capture the time variation in expected returns. In support of that assertion, these conditioning variables have been related to longer horizon returns of monthly, quarterly, or annual frequencies. In contrast, the *EEP* forecasts returns at daily horizons when expected returns are unlikely to vary significantly. Moreover, to the extent that informed investors trade in the options market (Black (1975)) and that information does not diffuse instantaneously across markets (Shiller (2000), Sims (2001)), the predictability may be due to the *EEP* containing information about changes in expectations about future fundamentals rather than time-varying expected returns.

Third, we analyze the source of this forecasting relation using two alternative approaches. First, we use Campbell's (1991) VAR framework and decompose realized returns into expected returns and shocks to dividend growth, excess returns, and interest rates. We find that the *EEP* predicts mainly the dividend shock component of the underlying index return. This result supports the conjecture that the call *EEP* captures changes in expectations about future cash flows of the underlying index. In a second approach, rather than relying on a return decomposition, we test directly whether the *EEP* captures fluctuations in future dividend growth. The results not only collaborate the VAR findings that the *EEP* forecasts fluctuations in future dividend growth but they also suggest that the predictive signal in the *EEP* is concentrated right before dividends are announced. In sum, both the VAR and the direct regression approaches link the predictability of the underlying returns by an option market variable to cash flow news. To our knowledge, this link has not been previously established.

The last two results lead us to the conclusion that the call *EEP* is positively related with subsequent underlying index returns at daily frequency mainly because it contains information about future cash flows. These findings support Black's (1975) conjecture that informed investors prefer to trade in the options market. The fact that we don't observe predictability beyond two-day horizons implies that the options and the underlying markets are reasonably well-integrated. The last two findings are also consistent with the first empirical and simulations results, which suggested that the *EEP* is sensitive to changes in cash flows. Our results support the claims of Kothari and Shanken (1992) and Torous, Valkanov, and Yan (2005) who argue that the commonly used proxy for expected future dividends may contain measurement error and are too smooth to forecast future returns at short horizons. The *EEP* responds rapidly to changes in cash flows and is thus more suitable to detect short horizon predictability. In sum, the novel contributions of this paper are to propose the call *EEP* as a short horizon predictor of the underlying return, to argue for the economic reasons behind the predictability, and to provide supporting empirical evidence. More broadly, we establish predictability of the underlying returns with an options market variable, and link this predictability to information about cash flows fundamentals, and thereby provide clear support to the Black (1975) conjecture.

The paper is structured as follows. We describe the dataset in Section 2. In section 3, we present summary statistics of the *EEP* and use simulations to show that important statistical properties of the *EEP* can be replicated when dividends, volatility, and interest rates are calibrated to the data. In section 4, we present the predictability results and link them to the ability of the *EEP* to forecast changes in future dividend growth. We conduct a series of robustness checks in Section 5 and conclude in Section 6 with some final remarks.

2 Data

We have three types of time series: values of the FTSE 100 index, prices of European and American calls and puts on the FTSE 100 index, and other variables, such as short interest rate, the lumpy dividend stream of the FTSE 100 index and the volume of its shares traded, and the implied volatility of the index. We describe each time series separately for clarity.

FTSE 100 Index and Index Futures: We compute daily log returns of the FTSE 100 cash index over a four-year period from June 1992 to January 1996. All the stocks are traded at the London Stock Exchange (LSE). The log returns exclude dividend payments. The index return in excess of the one-month (riskfee) UK interest rate is denoted by R_t. We also compute the daily log return of the FTSE 100 index futures,[7] which is traded at the London International Financial Futures Exchange (LIFFE). The index futures return is denoted by R_t^{fut}.

FTSE 100 Index Options: We have all the bid-ask quotes recorded for all European and American FTSE 100 index options traded on the London International Financial Futures Exchange from June 1992 to January 1996. Since these contracts were heavily traded, there were no designated market-makers obliged to stand ready to buy and sell. Liquidity in these markets was generated in a CBOT-style auction hand-signal pit-trading environment with voluntary dealers and direct interaction of buyer's and seller's agents. Nothing in this process should generate any microstructure-related systematic differences between European

[7] The returns are computed from the "on-the-run" contracts. We roll over to the next on-the-run contract one month before the current on-the-run contract expires.

and American prices. To minimize possible data errors and to make all contracts comparable, we apply several filters. For instance, we use only synchronous quotes of the European and American option, or quotes that are posted within 60 seconds of each other. This results in a sample of 47960 matched quotes for call options and 41270 matched quotes for put options. We also exclude prices lower than the intrinsic values. Furthermore, if we define moneyness as the spot price divided by the strike price, S/K, we use only options that are within the range 0.9 and 1.1. Finally our data includes 41891 matched pairs of calls and 35961 matched pairs for puts.

The European and American index option contracts have identical exercise dates. At any time there are five different maturities of both types of options, one month, two months, three months, four months and a long-dated one. For a given maturity, American option exercise prices are multiples of 50 while European option exercise prices are multiples of 25 but not 50. In order to directly compare the prices of the American and the European option, we linearly interpolate the prices of the two adjacent American options whose strike prices straddle the strike price of the European option that we are trying to estimate. With this method, we obtain the synchronous prices of American and European contracts with the same strike price and maturity.

The early exercise premium is computed as the difference in prices between two otherwise identical American and European options, normalized by the price of the European contract. We use the normalization mainly because the non-normalized difference is affected by the index level, the volatility, and other variables that enter the option pricing formula. Through the normalization, we control for the level of these variables and measure the premium of the American relative to the European contract. We are careful not to normalize by the level of the index itself, because doing so would induce an automatic correlation with next-period index returns.

Instead of tracking every contract every day, it is more appropriate to aggregate the information according to the moneyness and maturities. Since no single option has the same moneyness on every single day, we compute the EEP for standardized at-the-money options, which is a natural benchmark. For every trading day, we linearly interpolate the EEPs of all the matched pairs on that day in the moneyness space and use the fitted value of the EEP at the moneyness equal to 1 as the EEP measure for at-the-money options on that day. In this way, we construct a time series of 894 daily EEPs, which explicitly use information from options that are in and out of the money.[8] It might also be tempting to interpolate the data along the maturity space and construct a constant maturity EEP. Unfortunately, this is not a straightforward exercise, because in the presence of lumpy dividends, the relation between maturity and the EEP depends crucially (and non-linearly) on the timing of dividends. Since a simple interpolation procedure cannot take this dependence into account, we present most of the results without interpolating along the maturity space. Results from a linearly-interpolated, constant maturity EEP and from an average EEP of all contracts in a day, presented in the robustness section, produce very similar (and sometimes more significant) results.

The American index option holders also have a wildcard option. During the sample period, London option market's close was 4:10pm and London stock market's close was 4:30pm. American index option holders have the right to exercise (but not trade) the option up to 4:31pm at a settlement price based on the index level either at 4:10pm or later.

Dividends and Other Variables:

We have daily data of the one-month stochastically detrended U.K. interest rate (Rf_t) (following Campbell (1991)), the dividend yield distributed to index holders (DY_t), the implied variance of the index portfolio return (Var_t), and the changes in volume of FTSE 100 shares traded (ΔVlm_t). The stochastically detrended short rate is obtained by subtracting a

[8] While this interpolation introduces a bias in the EEP measure (because the EEP is not exactly linear in the moneyness space), the bias is not large in economic or statistical terms. We also provide further robustness check for this interpolation method.

lagged 3-month moving average from the raw one-month interest rate, similarly to Campbell (1991). Var_t is implied daily from closest to the money European call options.[9]

To understand the source of the lumpiness and uncertainly in dividends, it is necessary to understand the LSE regulations. Over our sample period, the LSE synchronized the ex-dividend dates across all firms to fall on the first trading day of the week. Any company that planned to go ex-dividend had to declare that via a Regulatory Information Service no later than four business days before the ex-dividend date, otherwise the ex-dividend date had to be deferred until the following week. From the dividend stream, we construct one-month moving average of the dividend and then compute the dividend price ratio. The lumpiness in the dividends series is due to two factors. First, in our sample, ex-dividend dates occurred typically every other week. Because of this mandated synchronization, the dividend price ratio is distributed about once every two weeks rather than uniformly. Second, U.K. companies typically pay out semi-annually (rather than quarterly, as in the U.S.). This creates additional lumpiness as well as uncertainty in dividends. Finally, while the dividend series are ex-post persistent, there is a significant ex-ante uncertainty about their actual realizations, which is a product of concern for a lot of financial analysts who follow LSE-listed firms. In that respect, the U.K. and the U.S. stock markets are quite similar.

3 The *EEP*: Magnitude and Dynamics

3.1 Summary Statistics

In this section, we describe the statistical properties of the early exercise premium. Table 1 presents the summary statistics of the *EEP* for calls and puts. To facilitate comparison, all

[9]Easley, O'Hara, and Srinivas (1998) provide a theoretical model and convincing evidence that options volume is related to future underlying returns. Unfortunately, we do not have historical FTSE 100 option volume data.

numbers are expressed in annualized percents except the *EEP*s and the trading volume.[10] We see that the average *EEP* of calls and puts is very different from zero. For calls, the *EEP* is 3.5 percent with a standard deviation of 1.8 percent. The *EEP* of puts is even higher at 7.6 percent with a standard deviation of 4.3 percent. In comparison, the average annualized return of the FTSE 100 index is 9.6 percent with a standard deviation of 12.5 percent and the average annualized dividend yield is 4 percent with a standard deviation of 2.2 percent. The *EEP*s are more volatile, very skewed and exhibit significant kurtosis compared to the returns of the underlying asset. This is due to the convex payoff of options and to their natural leverage.

In Panel B of Table 1, we display the partial autocorrelation functions of the *EEP*s, the index return and the index futures return. Column 1 shows the autocorrelations for call *EEP* and column 2 shows that of the put *EEP*. For calls and puts, the *EEP*s are positively serially correlated and the correlations are significant at up to 5 daily lags. In contrast, the FTSE 100 returns are uncorrelated at all but one-day lag, as can be seen from their autocorrelation which is displayed in the column 3. Finally the last column shows that the partial autocorrelation of the index futures returns are close to zero at all lags.

The observed serial correlation in the *EEP*s implies that the difference in European and American prices is not white noise. Since the *EEP* will not be zero when the dividends are non-zero or are paid in lump sums, we conjecture that the persistence might be due to dividend shocks. Whether the empirically observed serial correlations can be generated by dividends is an issue that we tackle next.

3.2 Explaining the Magnitude and Dynamics of the *EEP*

It is interesting to know whether *EEP*s of such magnitudes and with such statistical properties can be obtained using calibrated option pricing models. Geske and Johnson

[10] We multiply the daily returns by the number of trading days, 252.

(1984), Kim (1990), Carr, Jarrow, and Myneno (1992), Geske and Roll (1984), Barone-Adesi and Whaley (1987), Gukhal (2001) and several others study the theoretical pricing of the American call and put options.[11] The first three papers mainly focus on the pricing of American put options and almost all of them assume that the dividend yield is continuous because this assumption simplifies the modeling of the option prices. Allowing for lump-sum dividends leads to a problem that generally does not have a closed-form solution. So does allowing for realistic fluctuations in the conditional variance and risk-free interest rate.

In this paper, we take a different approach. We use the Longstaff and Schwartz (2001) simulation method to value American and European options, and then compute the *EEP*. Besides its simplicity, the Longstaff and Schwartz (2001) approach is appropriate in our study for two reasons. First, it allows for flexible and realistic calibration of the conditional variance and dividends of the underlying security as well as the risk-free interest rate. Second, our goal is to understand how the *EEP* varies with respect to the underlying parameters rather than finding the exact solution to the American option pricing problem. Therefore, calculating the *EEP* numerically and drawing comparative statistics serve our goal well.

We conduct two simulations. First, we examine how the dividend yield and volatility affect the *EEP* in a constant dividend yield Black-Scholes model. The goal of this exercise is to see whether realistic magnitudes the lumpy dividends and volatility can generate the empirically observed magnitudes of the average *EEP*. In this simulation, we assume that the stock price follows a geometric Brownian motion and the interest rate, the dividend yield and the volatility are all constant. The underlying stock will pay a lumpy dividend in two weeks. Under this setting, we calculate the price of a one-month at the money American option with the Longstaff-Schwartz simulation. Then we compare it with the price of an European option with the same contract details and obtain the *EEP*.

Figure 1 plots the magnitude of the *EEP* for different magnitudes of the dividend yield

[11] These papers attack the problem by solving a partial differential equation with a moving boundary which is a problem that generally does not have a closed-form solution.

and volatility. The top panel shows that the levels of the simulated call *EEP* are close to the average *EEP* that we observe in the data. For instance, when we set the dividend yield and the volatility to their average values from the data (4% and 12%, respectively), our simulation generates an *EEP* of 0.028. Recall that, in Table 1, the mean of the call *EEP* is 0.035. Similar results obtain for the put *EEP*, shown in the bottom panel of the figure.

Figure 1 also illustrates the sensitivity of the *EEP* to changes in the dividend yield and volatility. In the top panel, the call *EEP* surface is monotonic in both directions. The call *EEP* increases with the dividend yield. This is intuitive because, as the dividend yield increases, American option holders are more incentivized to exercise before ex-dividend date in order to profit from the high dividends, which raises the premium. Importantly, when volatility is in the 0.10 to 0.15 range, the call *EEP* is more convex in the level of the dividend yield. Hence, in normal volatility regimes, the *EEP* is very sensitive to changes in the dividend yield.

The call *EEP* is quite flat in the volatility space when the dividend yield is low and decreases with volatility when the dividend yield is high. This latter effect is due to two factors. First, volatility boosts the option value when American option holders face the exercise decision and reduces the chance of exercising early. Second, our *EEP* measure scales the absolute premium by the price of the European contract which increases with volatility. For put options, the *EEP* is decreasing in the dividend yield as higher dividends will reduce the incentives for early exercise. The put *EEP* is also decreasing in volatility for the same reasons as calls.

In a second simulation, we examine the dynamics of the *EEP* under the risk-neutral measure when the interest rate and dividend yield follow an AR(1) process and the volatility follows a GARCH(1,1) process. More specifically, we investigate whether we can reproduce the serial correlation in the *EEP* observed in the data. To do so, we generate the risk-free rate, dividend yield, and conditional volatility from

$$\begin{aligned} Rf_{t+1} &= \phi Rf_t + v_{t+1} \\ DY_{t+1} &= \rho DY_t + u_{t+1} \\ \sigma^2_{t+1} &= \kappa + \alpha\varepsilon^2_t + \beta\sigma^2_t. \end{aligned}$$

where Rf_{t+1} is the risk-free rate, DY_{t+1} is the dividend yield, and σ^2_t is the variance of excess returns. α and β are the GARCH(1,1) coefficients for σ^2_t, and ϕ and ρ are the AR(1) coefficients for the risk-free rate and the dividend yield, respectively. There is no risk premia for the state variables. Under this dynamic setting, we simulate the underlying asset for 1000 steps, re-price the same American option as above, and calculate the *EEP*. From the simulations we obtain a time series of the *EEP* and calculate the AR(1) coefficients of the call and the put *EEP*, respectively.

Table 2 shows the simulation results of the AR(1) coefficients of the call and put *EEP* for a set of different parameters of the data generating processes. The first row uses the parameters that are estimated from our data. The call *EEP* has an AR(1) coefficient of 0.361 which is remarkably similar to the one from the data (0.377). In the second set of rows, we vary the persistence of the volatility. The third and fourth set of rows show similar results for various persistence levels of the risk-free rate and the dividend yield, respectively. These simulation shows that the more persistent are the volatility, the dividend yield and the interest rate, the higher is the AR(1) coefficient of the call *EEP*.

In particular, the serial correlation of the call *EEP* is very sensitive to the persistence of the dividend yield process. A change in ρ from 0.906 to 0.800 results in a drastic reduction of its AR(1) coefficient from 0.361 to 0.084, which represents a decrease of 76.7 percents. The persistence of the risk-free rate and of the volatility have a more significant impact on the observed serial correlation of the put *EEP* than on the call *EEP*. For instance, a decrease in the GARCH parameter β from 0.890 to 0.800 results in a reduction of the AR(1) of the put *EEP* of 32.1 percents $((.171 - .252)/.252)$ and of the AR(1) of the call of 22.1 percents $((.281-.361)/.361)$. Since the ϕ and ρ parameters are likely to be downward biased (Andrews (1993)), using higher values of these parameters results in even higher serial correlation of both the call and the put *EEP*s.

These simulations suggest that the call *EEP* is particularly sensitive to the level and the serial correlation of the lump sum dividends. In particular, the ability to simulate an *EEP* process that, in the presence of lumpy dividends, is very similar to the data leads us to conjecture that unexpected fluctuations in the dividend yield process might be captured by the *EEP*. This is a hypothesis that we investigate in the next section.

4 The Information Content of the *EEP*

We have so far established the dependence and sensitivity of the *EEP* to variations in dividend yield, volatility, and interest rates. In this section, we address two natural questions. First, does the *EEP* contain information related to future returns of the underlying asset? Second, if such a relation exists, what is its provenance?

4.1 Predictive Regressions

4.1.1 Excess Market Returns

To investigate whether the *EEP* contains information about future stock returns, we run the daily predictive regression

$$R_{t+1} = \alpha + \beta EEP_t + \gamma X_t + \varepsilon_{t+1} \tag{1}$$

where R_{t+1} is the excess return between the FTSE 100 index return and the one-month UK treasury rate from t to $t+1$, EEP_t is the daily call EEP and X_t is a vector of additional predictive variables observable at t, such as the dividend yield (DY_t), the risk-free rate (Rf_t), the implied variance of the at-the-money option (Var_t), and the changes in its volume (ΔVlm_t). The dividend yield along with other variables might not act as perfect predictors especially at short horizon but they help us understand whether the EEP contains additional information and provide us a yardstick to measure the information content of the EEP.

The results from different specifications of the regressions are shown in Table 3 Panel A. In column 1, we display the benchmark case of the dividend yield as the only predictor of returns, because it has been used as a return predictor in numerous studies (e.g., Campbell and Shiller (1988b)) with U.S. data. The coefficient on the dividend yield is positive but not significant and the variable explains little variation in daily excess returns because the dividend yield is very smooth as discussed in Valkanov (2003). The t-statistics reported in parentheses below the estimates are computed using Newey and West (1987) heteroskedasticity and autocorrelation robust standard errors.

In column 2 of Table 3 Panel A, we add the EEP which measures the relative premium of American relative to European call options. Its coefficient is positive and statistically significant. This is one of the main results of the paper. Adding EEP also appears to improve the model fit as the R^2 increases to a modest level of 0.7 percent for a daily predictive regression. The sign is in line with what we expect from economic intuition and from the simulations displayed in Figure 1 and Table 2. A higher and persistent EEP implies that investors expect higher lump sum dividend payments and are ready to pay a higher premium for American relative to European options.

In column 3 to 5, we incrementally add other variables that are known to predict returns. In column 3, we include the lagged daily index excess return to test whether the observed predictability is due to a mechanical serial correlation in returns. The coefficient of the lagged return is statistically insignificant but it increases the R^2 of the regression. More importantly, its addition does not diminish the predictive power of the *EEP*, whose point estimate and statistical significance are almost unchanged. In column 4, we add the at-the-money European option implied variance and the risk-free rate. We include a measure of the conditional variance, because Ghysels, Santa-Clara, and Valkanov (2005b) show that it is positively related to future returns for the US stock market. The implied variance can also be interpreted as a proxy for the wildcard option that is included in the *EEP*. Fleming and Whaley (1994) model this wildcard premium explicitly and find that it is mostly affected by the volatility of the at-the-money option. Campbell (1991) argues that the risk-free rate is also a good predictor of excess returns because it is a proxy for variations of the investment opportunity set. In Table 3, the volatility and the risk-free rate estimated coefficients have signs that agree with studies for the US stock market, but they are not statistically significant. The lack of significance at the one-day horizon of these variables and of the dividend yield is not surprising, because they are persistent and have low variance and are thus better at predicting returns at monthly, quarterly, or annual horizons.

Finally, in column 5 we control for lagged changes in FTSE 100 share volume over the previous day as proxy for liquidity in the FTSE 100 market at day t. Amihud and Mendelson (1986) and Pastor and Stambaugh (2003) show that liquidity has a large impact on future returns. In Table 3, high liquidity precedes lower future returns, which is consistent with previous findings. The change in volume is the only significant variable, in addition to the *EEP*. However, it must be noted that the inclusion of the change in volume does not alter the point estimate or the significance of the *EEP*. Hence, the *EEP* ought to capture information about future returns that is orthogonal to that in the other predictors.

Although the coefficient of the *EEP* is statistically significant, its magnitude might appear small when compared to the benchmark forecaster, the dividend yield. To understand the economic magnitude of the predictability, it is helpful to compare the impact of a one-standard-deviation shock in each one of these variables to excess returns. A one-standard-deviation shock to the dividend yield results in 4.9 basis points ($0.350 \times \frac{0.022}{\sqrt{252}}$) increase in next day's index return. A similar shock to the *EEP* produces a 6.5 basis points change (0.036×0.018) in next period's returns.[12] Hence, at a daily basis, the economic significance of the *EEP* is almost 50 percent higher than that of the dividend yield. The coefficient on the change in volume is difficult to compare to the *EEP* because it is not in percents.

To summarize the findings in Table 3, all variables enter with the economically expected sign in predicting the FTSE 100 index return and replicate studies for the US stock market. However, the only significant predictor at the daily frequency is the *EEP* and the changes in trading volume. Whether the forecasting ability of the *EEP* is spurious or the result of various microstructure issues is something we investigate extensively below.

4.1.2 Index Futures Returns

We have shown that the *EEP* predicts the market excess returns at a daily horizon. However, there are two potential issues with the FTSE 100 stock index results. First, they may be due to non-synchronous trading. Indeed, some stocks in the index may not trade in the closing hour of the market and therefore our results from the cash index may be due to stale quotes. Second, in our sample period, the stock market trading ceases at 4:30pm and the options market closes at 4:10pm. Although the stock market closes later than the derivative markets and we are not using any future information when conducting our prediction study, it is interesting to investigate whether the return predictability we found is caused by the movement of the stock market between 4:10pm to 4:30pm. Since this 20-minute window is also the period when the wildcard option can be exercised, investigating the exact timing provides us one more way to control the effects of the wildcard option.

We address both of these issues by using the returns of the FTSE 100 index futures. This futures index is not subject to the non-synchronous trading problem. Table 1 Panel

[12] The standard deviations of the variables are in Table 1.

B indicates that the index futures returns exhibit little autocorrelation even at one-day lag. This implies that the returns of index futures do serve our goal well in mitigating the caveat of stale prices. This is not surprising because the futures contracts are actively traded with high liquidity. Moreover, the futures market closes at 4:10pm similarly to the options market.

Table 4 Panel A shows the same predictive regressions that are in Table 3 but the forecasted variable is the $FTSE100$ futures, instead of the spot, return. In all specifications, our main predicting variable, the EEP, is economically and statistically significant. The coefficients of the EEP are all equal to 0.043 across all specifications and they are about 15% higher than those in the market excess return prediction. Economically, the EEP is more important in predicting the returns of the index futures and the statistical significance is comparable with the previous case. All other predicting variables remain insignificant except the changes in trading volume. One thing worth noting is that the point estimate of the lagged return is negative and very close to zero. In other words, using the index futures returns does help us eliminate the non-synchronous trading problem. More importantly, we clearly see that our predictability is not due to the 20-minute return before the stock market close. Therefore, it precludes the possibility that the documented predictability is due to the wildcard option.

In summary, the predictability of the EEP is strengthened in forecasting the index futures returns. This predictive power is not caused by the wildcard option or potential non-synchronous trading in the cash index.

4.1.3 Returns at Longer Horizons

We have shown that the EEP predicts the market excess returns and the index futures returns of the following day. Here we investigate longer horizon predictability for two reasons. First, it is interesting to see how rapidly information diffuses from the options market to the underlying asset. Second, it is possible that microstructure-related dynamics could potentially generate spurious predictability. In this section, we address these issues by examining whether the *EEP* predicts the excess market and the index futures returns at horizons of two days, three days, and up to two weeks.

In Panel B of Tables 3 and 4 we display the results for excess market returns and index futures returns. Since the two sets of results are virtually the same, we will focus on the case of index market returns in Panel B of Table 3. Column one in that panel contains the results from a forecasting regression of two period returns, $R_{t+1,t+2}$. The point estimate of the *EEP* is 0.035, slightly lower than the estimate of 0.036 obtained in the one period regressions. The t-statistics and the R^2 are also lower. In column 2 to 4, we present the results where the forecasted variable is $R_{t+2,t+3}$, $R_{t+3,t+4}$, and $R_{t+4,t+5}$, respectively. The coefficients of *EEP*s in these regressions are even lower and become statistically insignificant. The explanatory powers also declines. The forecastability completely disappears at horizons longer than three days. Finally in column 5, in the forecast of $R_{t+6,t+10}$, the coefficient of the *EEP* goes down further and the *EEP* does not carry any predictive power for the next week's weekly return. The high R^2 is evidently due to the overlapping of the weekly returns.

The longer horizon results suggest that the forecastability of the *EEP* is mostly observable at horizons of one and two days. At longer horizons, the magnitude of the *EEP* coefficients decreases gradually and becomes insignificant after two days or so. This pattern suggests that it takes about one to two days for the stock market to digest the information in the *EEP*. The fact that our findings are robust even when we include the lagged returns makes it unlikely that the result is due to market microstructure effects. Given the results in this section, from now on we concentrate on one-day returns, R_{t+1}.

4.2 The Provenance of the Predictability

We conjecture that the predictive power of the *EEP*, documented in the previous sub-section, is due to its sensitivity to changes in expectations about future lump sum dividend payments.

We test this conjecture below using two alternative approaches. The approaches differ with respect to the identification and frequency of the dividend growth shocks. However, the empirical results are remarkably similar which indicates that our findings are a robust feature of the data.

4.2.1 The Campbell-Shiller (1988) Decomposition

The *EEP* predictability of FTSE 100 returns is at short horizons. In order to identify the source of this predictability, we use the structural VAR approach of Campbell and Shiller (1988a) and Campbell (1991). More specifically, we specify a vector z_{t+1} which contains the (demeaned) excess FTSE 100 returns, the DY_{t+1}, σ^2_{t+1}, rf_{t+1} and ΔV_{t+1}. Then we estimate the VAR, $z_{t+1} = A(L)z_t + w_{t+1}$ where $A(L) = A_1 + A_2 L + A_3 L^2 + ... + A_p L^{p-1}$. The residuals in vector w_{t+1} are the one-period ahead forecasting errors. More specifically, the first term in w_{t+1}, $w^{(R)}_{t+1}$ is the difference between the realized and the forecasted return, or $w^{(R)}_{t+1} = R_{t+1} - E_t(R_{t+1})$, where E_t denotes the conditional expectation formed from the VAR at the end of period t. However, $w^{(R)}_{t+1}$ has no economic interpretation.

The VAR results are shown in Table 5 where $p = 1$ and the order of the VAR was chosen with sequential pre-testing. The first column is similar to Table 3 with the exception that the *EEP* is omitted from the system. We do not include the *EEP* in the VAR because our goal is to understand whether it forecasts $E_t(R_{t+1})$ or some components of w_{t+1}. Including the *EEP* in the VAR would imply that, by construction, it would be uncorrelated with the residuals w_{t+1} and it would be correlated with $E_t(R_{t+1})$. There are also economic reasons for not including the *EEP* in the set of conditioning information. First, the *EEP* is not directly observable for most assets. Unlike the dividend yield, the short rate or the conditional variance, it is virtually inaccessible to investors. Second, as argued above, the *EEP* is unlikely to be a good proxy for expected returns as are the other variables in the VAR.

Following Campbell and Shiller (1988b) and Campbell (1991), we use a linearized version of the dynamic Gordon growth model to decompose unexpected returns into innovations due to changes in dividend growth, changes in discount rates, and changes in interest rates. If rf_t is the log risk-free rate and d is the log dividend, then we can write

$$\begin{aligned} w_{t+1}^{(R)} &= R_{t+1} - E_t(R_{t+1}) \\ &= (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j rf_{t+1+j} - (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j R_{t+1+j} \\ &= \eta_{d,t+1} - \eta_{Rf,t+1} - \eta_{R,t+1}, \end{aligned} \tag{2}$$

where Δ denotes a one-period difference, and the linearization parameter ρ is a constant related to the long-run dividend yield and it is smaller than 1. This equation has the following economic interpretation. If the unexpected return is positive, then either expected future dividend growth $\eta_{d,t+1}$ must be higher than previously expected, or the risk-free rate $\eta_{Rf,t+1}$ must be lower than expected, or the excess future returns $\eta_{R,t+1}$ must be lower than expected, or any combination of these three must hold true.

After estimating the VAR, the ex-post return is $R_{t+1} = \hat{E}_t(R_{t+1}) + \hat{\eta}_{d,t+1} - \hat{\eta}_{Rf,t+1} - \hat{\eta}_{R,t+1}$ where "ˆ" denotes the estimated values. Since R_{t+1} is forecastable by the *EEP*, it is interesting to investigate where the forecastability is coming from. We note that while $\hat{E}_t(R_{t+1})$ is uncorrelated by construction with $\hat{\eta}_{d,t+1}$, $\hat{\eta}_{Rf,t+1}$, and $\hat{\eta}_{R,t+1}$, the latter three shocks to returns are correlated.

To disentangle the source of the predictability, we regress the four components of realized return, $\hat{E}_t(R_{t+1})$, $\hat{\eta}_{d,t+1}$, $\hat{\eta}_{Rf,t+1}$, and $\hat{\eta}_{R,t+1}$ on the previous day *EEP*. The results from these regressions are reported in Table 6. The *EEP* forecasts changes in the dividend growth process. The coefficient in front of $\hat{\eta}_{d,t+1}$ is positive and significant. These results are in agreement with economic intuition and the simulation results in section 3. Higher unexpected lump sum dividends lead to a larger American option premium and larger *EEP*, as the American contract is more likely to be exercised prior to the ex-dividend date in order to take advantage of the larger dividend payout. As we will see below, this result is a robust feature of the data. This finding is also consistent with the findings in Amin and Lee (1997), who document that option traders initiate a greater proportion of long (short) positions a few days before good (bad) earning news.

The *EEP* does not forecast changes in expected excess returns. The coefficient on $\hat{\eta}_{R,t+1}$ in Table 6 has a positive but insignificant sign. The sign of the coefficient in front of $\hat{\eta}_{Rf,t+1}$ is negative but also insignificant, which implies that an increase in the *EEP* leads to an (insignificant) increase in future returns through an unexpected lowering of the interest rates.[13] Finally, the *EEP* is negatively correlated with forecasted next day returns, $\hat{E}_t(R_{t+1})$. The coefficient is negative and is only significant at the ten percent level. The negative estimate is probably due to the fact that the forecasted daily returns are a noisy proxy of expected returns, which are better estimated at longer horizons. The sub-sample findings presented in Table 6 will be discussed in the robustness section.

If we take the results from Table 6 at face value, the forecasting ability of the *EEP* is due to its significant correlation with future changes in dividend growth. To understand the economic significance of this correlation, we compute the effect of a one standard deviation shock of *EEP* on subsequent returns. For the dividend growth, this is 7.2 basis points (0.040×0.018). The standard deviation of $\hat{\eta}_{d,t+1}$ in the VAR is 97 basis points. In other words, a one standard deviation shock of *EEP* leads to an almost 10% change of the volatility of $\hat{\eta}_{d,t+1}$.

4.2.2 An Alternative Method

We have thus far showed that the *EEP* forecasts future changes in the dividend growth process, where the innovations in dividend growth were obtained using the Campbell and

[13] Lower unexpected interest rates lead to higher returns. Note that $\hat{\eta}_{Rf,t+1}$ enters with a negative sign in equation (2).

Shiller (1988a) VAR decomposition. It is reasonable to ask whether this decomposition accurately identifies the dividend growth innovations in returns. To answer this question, we take a more direct empirical approach at isolating dividend growth shocks. Using the FTSE 100 dividends, D_t, we construct a series of dividend growth rate, $DG_t = log(D_t) - log(D_{t-1})$. The dividends are available on the ex-dividend date for the FTSE 100 index. If the hypothesis that the *EEP* contains information about future dividend growth rates is correct, then the daily EEP series must forecast fluctuations in the DG_t series. The advantage of this approach is that the DG_t series is directly observable and does not have to be identified from the returns series.

Two obstacles stand in our way of investigating more directly whether the *EEP* forecasts fluctuations in dividend growth rates. First, as mentioned above, the lumpy DG_t series are available at bi-weekly frequency, whereas the *EEP* series are daily. Aggregating the *EEP* to a bi-weekly horizon is not suitable in this case, because as shown in Table 3, the forecasting relation occurs at frequencies of no more than a couple of days. In other words, running the forecasting regressions at bi-weekly frequency would obfuscate the daily lead-lag effect. Second, there are seasonalities in the dividends and dividend growth processes, which might produce spurious correlation in a forecasting relation.

To address both of these concerns, we use the following mixed data sampling (MIDAS) regressions (Ghysels, Santa-Clara, and Valkanov (2005b)).

$$DG_{Ht} = \alpha + \phi(L)DG_{H(t-1)} + \gamma \sum_{k=1}^{K} \beta(k,\theta)EEP_{t-k} + e_t \tag{3}$$

where $\phi(L) = 1 + \phi_1 L + \phi_2 L^2 + \ldots \phi_p L^p$ is a polynomial in L of order p. The subscript of DG_{Ht} reflects the fact that the dividend growth rate is available only once every H periods. In our case, $H = 10$ or the dividend growth rate is observable once every two weeks. The AR(p) component captures seasonal components in DG_{Ht}. The second part of the regression, $\gamma \sum_{k=1}^{K} \beta(i,\theta)EEP_{t-k}$, is the MIDAS term. In that expression, we use lagged daily *EEP*s to forecast the bi-weekly dividend growth rates. In other words, the dividend growth rate of, say, July 1st, 1995 will be regressed on p own lags as well as on lagged daily EEP rates starting June 30th and going back K days.

Since the number of lagged daily EEPs needed to capture the dynamics of the dividend growth rate might be large, the unrestricted specification of the weights results in a lot of parameters to estimate. The cost of parameter proliferation is that the estimates will be estimated imprecisely and the regression will produce poor out-of-sample forecasts. To reduce the number of coefficients to estimate, we follow the MIDAS regression approach and parameterize the lags in front of the EEP_{t-k} using a function $\beta(k, \theta)$. The lag function is parsimoniously parameterized and its parameters are collected in a vector θ. Ghysels, Santa-Clara, and Valkanov (2005a) show that a suitable parameterization $\beta(k, \theta)$ circumvents the problem of parameter proliferation and of choosing the truncation point K. We also normalize the weights $\beta(k, \theta)$ to add up to one, which allows us to estimate a scale parameter γ. The normalization is useful because γ captures the overall predictive power of lagged EEPs, while the dynamics of the EEPs is captured by the weights.

In general, there are many ways of parameterizing $\beta(k, \theta)$. We focus on the Beta function specification (also used by Ghysels, Santa-Clara, and Valkanov (2005a)), which has only two parameters, or $\theta = [\theta_1; \theta_2]$:

$$\beta(k, \theta) = \frac{f(\frac{k}{K}, \theta_1; \theta_2)}{\sum_{j=1}^{K} f(\frac{j}{K}, \theta_1; \theta_2)} \tag{4}$$

where $f(z, a, b) = z^{a-1}(1-z)^{b-1}/\beta(a, b)$ and $\beta(a, b)$ is based on the Gamma function, or $\beta(a, b) = \Gamma(a)\Gamma(b)/\Gamma(a+b)$. The flexibility of the Beta function is well known. The function is often used in Bayesian econometrics to impose flexible, yet parsimonious prior distributions. It can take many shapes, including flat weights, gradually declining weights as well as hump-shaped patterns. While MIDAS regressions are not limited to Beta distributed lag schemes, for our purpose we focus our attention on this specification. We refer to Ghysels, Santa-Clara, and Valkanov (2004, 2005b) for alternative weight specifications.

The predictive MIDAS regression (3) and (4) is estimated by quasi maximum likelihood and the results are reported in Table 7. In the first column, we report the baseline case of regressing the dividend growth rate on three of its lags with no lagged *EEPs* (no MIDAS terms). The order of the lags was selected by sequential pre-testing. The estimated lag coefficients are all significant which confirms our assertion that the dividend series contain seasonal components. The R^2 of this regression is 0.297.

In the second column of Table 7, we add the lagged daily *EEP*s, where K is set to 45 days, or two months' worth of daily returns.[14] If the conjecture that the early exercise premium contains information about future dividend growth is correct, then we expect the γ coefficient to be positive and statistically different from zero. Consistent with this conjecture, we obtain a γ estimate of 3.093. This estimate is statistically significant at the 1 percent level. A joint F-test of the significance of all the MIDAS parameters (γ, θ_1, and θ_2) being equal to zero is also statistically significant at the 1 percent level. Since the $\beta(k, \theta)$ function is normalized to sum to one, we can interpret the coefficient estimates of γ as the total impact of the lagged EEPs on future dividend growth.

The parameter estimates θ_1, and θ_2 are difficult to interpret because they have no economic meaning. In contrast, the shape of the polynomial $\beta(k, \theta)$ has a clear economic interpretation. It captures the rate at which information is incorporated from the *EEP*s into the dividend growth component. The shape can be interpreted as the impulse response of the dividend growth rate to *EEP* fluctuations. The estimated $\beta(k, \theta)$ plotted as a function of the daily lags is displayed in Figure 2 using estimates of θ_1, and θ_2 from Table 7. A few interesting findings emerge.

First, most of the mass is concentrated on only four to five daily *EEP*s, which suggests that the predictability is at short horizons. Otherwise, we would expect to see more weight

[14]We experimented with K as large as 130 days (about 6 months) and the results were almost identical.

on a larger fraction of lagged *EEP*s. Second, the location of the mass is on *EEP*s between 15 and 18 days before the ex-dividend date. Dividend payments for the FTSE 100 index stocks are announced between 10 to 15 days before the ex-dividend date. That period is represented in shaded pattern on the figure. The shape of the estimated weights clearly shows that most of the predictability occurs right before the announcement period, which suggests that our MIDAS procedure accurately captures the timing of when information is incorporated into prices. To summarize the findings in the figure, the concentration of the mass and the location of the weights corroborate the evidence from the previous section that the predictability is at short horizons and it is due to news about dividend growth rates.

4.3 Discussion and Related Literature

The *EEP* forecasts the underlying returns at short horizons. Moreover, its predictive ability is related mostly to innovations to the dividend growth component of returns rather than discount rates or expected returns. Both of these findings are consistent with the view that information about future cash flows is first revealed in option prices rather than in the price of the underlying security. This result is consistent with Black's (1975) view that informed investors prefer to trade in the options market. Moreover, the very short horizon nature of the predictability indicates that while information does not flow instantaneously between the options and the underlying markets, it is incorporated quite efficiently.

Informed trading might be even more prominent in individual stocks than in the stock index. However, on any ex-dividend date, at most a fraction of the companies go ex-dividend. From that perspective, trading in the index is a close but not perfect substitute to trading in the individual stock with a lower price impact. Also, the predictability that we observe at the index level is likely to be an attenuated version of the information diffusion we would observe if we had data for individual stock options. Unfortunately, as mentioned above, the FTSE 100 index is the only asset with comparable European and American option contracts.

The daily lag in the information flow is consistent with Sims (2001) and Shiller (2000) who explore the implications of limited information-processing capacity for asset prices. These authors argue that investors, rather than possessing unlimited-processing capacity, are better characterized as being only boundedly rational. The inability of investors to immediately incorporate all relevant information into prices gives rise to short horizon predictability across markets. Hong, Torous, and Valkanov (2004) make a similar point by linking the slow diffusion of cash flow information across industries to short horizon cross asset return predictability. We are the first to document a similar phenomenon in the options market, by linking the underlying return predictability to the *EEP*'s ability to forecast mainly innovations to dividend growth.

Our paper is related to several others that use option market information to forecast underlying returns. Manaster and Rendleman (1982) show that if we take the volatility as given and impute the implied stock prices from the options, this implied stock price will predict future stock return by one day. Anthony (1988) shows that shocks to option trading volume leads shocks to stock trading volume by one day. However, Stephan and Whaley (1990), Chan, Chung, and Johnson (1993) and others find no evidence that price changes in option markets lead price changes in the underlying. Easley, O'Hara, and Srinivas (1998) find that option market volume predict underlying returns which is consistent with the view that informed investors trade in the options market. Pan and Poteshman (2004) also find that option trading volume contains information about future stock price movements and argue that the source of the predictability is non-public information possessed by option traders. In relation to previous work, the novel contributions of this paper are: (i) the introduction of the call *EEP* as a short horizon predictor of the underlying return; (ii) to argue for the economic reasons behind the predictability; and (iii) to provide supporting empirical evidence that link the predictability to news about future cash flows.

The presented evidence may also be used to sharpen theoretical discussions that have followed Black (1975). For instance, Biais and Hillion (1994) show that theoretically the option market can be more or less informative about the underlying asset's payoff depending on the modeling assumptions. Moreover, Easley, O'Hara, and Srinivas (1998) show that, under certain conditions a pooling equilibrium exists where some informed traders choose to trade in both the options market and the underlying market. Their theoretical results in general support Black's intuition that the options market might convey some distinctive information. However, as Back (1993) pointed out, if the options market as well as the underlying market both work as in Kyle (1984), trades in the options will move the underlying market as well. However, our specific trading strategy has the property that it is neutral in the option market. It is long an American call and short an European call. If the American and European contracts have similar price impacts on the underlying market, then the long and short position will have virtually no price impact on the underlying index. Therefore the underlying market will not react immediately, which induces the lead lag relationship.

An alternative explanation for our findings might be that the early exercise premium is purely driven by irrational financial market behavior which also has an impact on underlying returns. While there is some evidence that individual customers engage in irrational exercising of options, Poteshman and Serbin (2003) show that larger traders exhibit no irrational exercise behavior. Hence, this is not a compelling explanation for the FTSE 100 index options which are widely held and traded by both individuals and institutional investors.

5 Robustness

In this section, we provide several robustness checks of the main results in Tables 3 and 6. Some of these tests are motivated by economic theory, while others address statistical concerns.

5.1 Subsamples: Pre- and Post-1994

To investigate the stability of our predictability results, we break the 1992-1996 sample into two sub-samples: June, 1992 to July 18, 1994 and July 19, 1994 to January 12, 1996. The July 19, 1994 break date was chosen for two reasons. First, the exchange changed its settlement system on that date and this resulted in a substantial change in the effect of short-selling restrictions. This change might affect the hedging and therefore the trading behavior of options.[15] Second, this date splits our sample into sub-samples with approximately equal number of observations.

Table 8 presents the predictive regression results in the two sub-sample periods. The entire sample results (from Table 3) are also displayed in the first column for convenience. We observe that the *EEP* predicts future FTSE 100 returns in both sub-samples even after controlling for all other commonly used predictors. Interestingly, the point estimates of the *EEP* coefficient in the sub-samples, 0.038 and 0.048, are very similar to that of the entire sample, 0.036. Importantly, the estimates remain statistically significant despite the short sub-samples. The slight reduction in the t-statistics is undoubtedly due to the fact that we have fewer observations in the two sub-periods, which decreases the power of our tests.

The stability of the forecasting relation that we document is quite remarkable, especially at short horizons. For instance, we notice that none of the other variables predict the FTSE 100 in both sub-samples. The coefficient on change in volume which was significant in the entire sample is also significant in the first subsample, but not in the second one.

To investigate whether the predictability in sub-samples is due to unexpected fluctuations in dividend growth, we re-do the VAR decompositions and present the results

[15] Prior to July 18, 1994, the LSE followed a fixed date (rather than fixed period) settlement regulation, in which all transactions within a two or three week "account settlement period" were settled on the second Monday of the following account settlement period, making ex-dividend dates two or three weeks apart. After July 18, 1994, even though the settlement system changed to settle 5 trading days after a transaction, ex-dividend dates have largely continued the historical practice of being only on the first day of the week, and typically every two weeks.

in the bottom two rows of Table 6. The results for the sub-periods are that higher *EEP* predicts higher future dividends. The *EEP* does not predict any of the other components in both sub-samples. These results are is in agreement with the findings from the whole sample and also with economic intuition. Remarkably, the point estimates in the sub-samples, 0.058 and 0.058, respectively, are identical to each other (to the third digit) and are also similar to the estimate from the entire sample, 0.040. In the first sub-sample, the coefficient on $\hat{\eta}_{d,t+1}$ is significant only at the 10 percent, probably because of the lack of power of the test in the short sample.

The sub-sample results in Tables 6 and 8 lead us to conclude that the predictive ability of the *EEP* is a robust feature of the data.

5.2 Put *EEP* Results

Thus far, our focus has mainly been on the call *EEP*, even though the dividend yield also has an impact on the *EEP* of put options. The concentration on the call *EEP* was guided by two main reasons. First, the *EEP* of put options are positive even when the underlying security does not pay dividends or when the dividend stream is continuous. In contrast, a positive call *EEP* can arise only when dividends are paid in lump sums. To put it differently, American put options can be optimally exercised earlier than maturity for reasons other than lumpy dividends. Therefore, the put *EEP* is not as sensitive and unambiguous an indicator of expected future dividends as is the call *EEP*. The second reason for not including put *EEP* in our main analysis is that higher dividend yields increase the cost of early exercising put options, all else equal. Indeed, we have seen in Figure 1 that the dividend yield impacts the *EEP* of call and put options in opposite directions.

With these arguments in mind, we expect that the predictive ability of the put *EEP* will be lower than that of the call *EEP* and the sign on the predictor will be reversed. In Table 9, we use the put *EEP* to run the same predictive regression as we did with the call

EEP (Table 3). As expected, the coefficient on the put *EEP* is negative, because higher put *EEP* indicates lower expected future dividends, everything else equal. Also expected is the fact that the put *EEP* coefficient is not statistically significant. While the point estimates are stable in the sample and across sub-samples, the t-statistics are never above one. As anticipated, the put *EEP* is a much noisier predictor of the underlying stock's returns, because it is a function of many other variables in addition to dividends.

The put *EEP* results serve as an additional robustness check that our findings are not spurious. Indeed, it may be argued that the predictability is due to market micro-structure differences between the options and the underlying market. The fact that we don't observe the predictability with put *EEP* is a clear demonstration that our results are not due to such automatic correlations and indirectly supports our main premise.

5.3 Alternative *EEP* Aggregation Methods

In the construction of our *EEP* variable, we do not control for the time-to-maturity of each contract. While the *EEP* certainly depends on the time span of the options, this dependence is complicated by the timing and lumpiness of the dividend payments and is therefore highly non-linear.

As an attempt to investigate the impact of the time-to-maturity on our results, we provide the following simple, albeit not fully satisfactory, robustness check. For every trading day, we linearly interpolate the *EEP*s of all the matched pairs on that day in the moneyness and time-to-maturity space and use the fitted value of the *EEP* at the moneyness equal to 1 and time-to-maturity equal to 1-month as the *EEP* measure for at-the-money constant maturity option on that day. With this new interpolation, we construct a time series of 894 daily *EEP*s. The daily interpolated, constant-maturity *EEP*s are denoted by EEP_t^{Mat}. As an alternative measure of the daily *EEP*s, we construct a daily *EEP* measure by averaging the *EEP* of all contracts every day. This daily averaged *EEP* serves as yet another robustness check. The daily averaged *EEP* is denoted by EEP_t^{Avg}.

Panels A and Panel B in Table 10 contain the results from the predictive regressions with these two new *EEP* forecasters. The predictive regressions also include the other forecasting variables. We provide the results for the entire sample as well as for the two sub-samples. The results in Table 10 are very similar to those of the previous tables in terms of magnitudes of the estimates as well as statistical significance. These additional robustness checks are reassuring that our results are not driven by the particular construction of the *EEP*.

6 Conclusion

In this paper, we use the call *EEP* to examine the information flow between the stock market and the derivative market. We first show that the empirically observed level and serial correlation of the *EEP* can be reproduced when the dividend yield process is lumpy and persistent. Therefore, it is reasonable to suspect that the observed *EEP* reflects the market participants' expectation about future dividends. We explore the information content of the *EEP* by asking whether the *EEP* forecasts the FTSE 100 index return. Based on the estimation results of time-series regression models, we further identify the source of this predictability.

Our results show that in a time-series regression the *EEP* predicts the underlying FTSE 100 index at daily horizon. Economically this forecasting relationship is about 50% higher than the widely used benchmark, the dividend yield. The economical and statistical significance is robust to the addition of other control variables. We conjecture that the *EEP* predicts the underlying asset's return because it is a forward-looking variable that contains the information about expected future dividends. We verify this hypothesis by decomposing the realized returns into expected returns and three different components of unexpected returns and find that the *EEP* indeed predicts the dividend shock component of the index return. This result confirms our hypothesis that the *EEP* reflects the option market's expectation about future fundamentals.

Traditional literature has studied the information flow between the options market and underlying asset market through option prices, volume and signed volume. Our study introduces the EEP as a short-horizon predictor of underlying returns, and links this forecastability to the fundamentals of the underlying market. This link provides a clear support for the Black (1975) conjecture that informed investors prefer to trade on their information about fundamentals in the options market rather than the underlying market.

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Table 1: Summary Statistics

Panel A reports the summary statistics for all the variables. EEP^{Call} and EEP^{Put} represent the EEP of call and put options. R_t is the FTSE 100 index return. R_t^{fut} is the FTSE 100 index futures return. DY_t is the one-month moving average of the dividend yield. Rf_t is the one-month stochastic detrended risk free rate. Var_t is the implied variance of the closest to the money European call option. ΔVlm_t is the change in share volume in million. All variables except ΔVlm are annualized. Panel B shows the partial autocorrelations of the call EEP, the put EEP, the index return, and the index futures return. The t-statistics are in the parentheses.

Panel A: Summary Statistics

	Mean	**Std**	**Skewness**	**Kurtosis**	**Observations**
EEP^{Call}	0.035	0.018	2.052	9.120	894
EEP^{Put}	0.076	0.043	2.384	10.491	894
R_t	0.096	0.125	0.210	2.663	916
R_t^{fut}	0.055	0.146	-3.082	3.892	916
DY_t	0.040	0.022	0.806	0.401	916
Rf_t	-0.001	0.004	-1.818	4.108	916
Var_t	0.025	0.011	1.442	5.911	894
ΔVlm_t	0.030	0.248	3.852	22.219	916

Panel B: Partial Autocorrelations of EEPs and Returns

Lag	$\mathbf{EEP}^{Call}$	$\mathbf{EEP}^{Put}$	R_t	R_t^{fut}
1	0.377	0.250	0.059	-0.018
	(3.840)	(4.213)	(1.889)	(-0.540)
2	0.184	0.223	0.045	-0.007
	(3.232)	(4.825)	(0.964)	(-0.198)
3	0.128	0.089	-0.022	-0.034
	(3.905)	(4.100)	(-1.073)	(-1.000)
4	0.009	0.165	0.032	0.005
	(0.152)	(4.633)	(0.628)	(0.135)
5	0.006	0.096	0.021	0.023
	(0.482)	(3.569)	(0.542)	(0.695)
10	0.074	0.043	0.004	-0.005
	(3.512)	(1.000)	(0.033)	(-0.159)
20	-0.020	0.025	0.017	0.023
	(-0.494)	(0.747)	(0.555)	(0.676)

Table 2: Simulating the Dynamics of the *EEP*

This table reports the dynamics of the *EEP* for calls and puts when the options are priced using numerical valuation. Its purpose is to illustrate the serial correlation in the *EEP* for various persistence levels of the underlying dividend yield, interest rate, and volatility processes. The parameters α and β are the GARCH(1,1) coefficients for the underlying asset's volatility. ϕ and ρ are the AR(1) coefficients for the risk-free rate and the dividend yield, respectively. Each sample simulates 1000 steps of the underlying asset. The *EEP*s for calls and puts are calculated and the AR(1) coefficients are obtained from the calculated results.

σ_t^2		Rf_t	DY_t	EEP^{Call}	EEP^{Put}
α	β	ϕ	ρ	$AR(1)$	$AR(1)$
0.104	0.890	0.992	0.906	0.361	0.252
0.104	0.800	0.992	0.906	0.281	0.171
0.104	0.700	0.992	0.906	0.240	0.070
0.104	0.890	0.900	0.906	0.117	0.020
0.104	0.890	0.800	0.906	0.095	0.016
0.104	0.890	0.992	0.800	0.084	0.099
0.104	0.890	0.992	0.700	0.073	0.036

Table 3: Predictive Regressions of Index Excess Returns

This table reports predictive regressions of excess returns by the early exercise premium and other forecasters for different horizons. The dependent variables are the excess return of the FTSE 100 index. DY_t is the one-month moving average of the dividend yield. EEP_t^{Call} is the early exercise premium of call options. R_t is the FTSE 100 index excess return (lagged). Var_t is the implied variance of the closest to the money European call option. Rf_t is the one-month stochastically detrended risk free rate. ΔVlm is the change in share volume (in million shares). The t-statistics in parentheses are corrected for hetroskedasticity and autocorrelation. Panel A compares the predictive regression of the next day's index excess returns under different specifications. Panel B examines the return predictability at longer horizons of up to two weeks using all the predictors (most exhaustive specification from Panel A). The numbers in the square brackets indicate the number of days the returns leading all the explanatory variables. For example, the column labeled $[2, 3]$ shows the regression of $R_{t+2,t+3}$ on all the explanatory variables at time t.

Panel A: Index Excess Returns

DY_t	0.511	0.350	0.492	0.313	0.490
	(0.162)	(0.111)	(0.165)	(0.104)	(0.163)
$\mathbf{EEP}_t^{Call}$		0.036	0.038	0.039	0.036
		(2.623)	(2.783)	(2.872)	(2.890)
R_t			0.074	0.071	0.078
			(1.432)	(1.345)	(1.476)
Var_t				5.717	5.716
				(0.830)	(0.827)
Rf_t				-5.076	-3.630
				(-0.321)	(-0.229)
ΔVlm_t					-0.512
					(-2.239)
R^2	0.000	0.007	0.012	0.014	0.018

Panel B: Longer Horizons

	[1, 2]	[2, 3]	[3, 4]	[4, 5]	[6, 10]
DY_t	0.917	0.249	-3.234	-2.075	1.437
	(0.300)	(0.079)	(-0.993)	(-0.702)	(0.743)
$\mathbf{EEP}_t^{Call}$	0.035	0.021	0.011	0.028	0.011
	(2.623)	(1.528)	(0.826)	(1.740)	(1.224)
R_t	0.043	-0.023	0.019	0.014	-0.035
	(1.208)	(-0.616)	(0.519)	(0.388)	(-1.950)
Var_t	-1.219	4.780	6.527	16.699	7.847
	(-0.140)	(0.553)	(0.753)	(1.724)	(1.112)
Rf_t	-15.267	-5.602	-3.371	8.125	-5.128
	(-0.947)	(-0.350)	(-0.203)	0.489	(-0.476)
ΔVlm_t	0.275	0.119	0.348	0.015	-0.103
	(0.959)	(0.598)	(1.680)	(0.064)	(-1.182)
R^2	0.010	0.004	0.006	0.012	0.020

Table 4: Predictive Regressions of Index Futures Returns

This table reports predictive regressions of excess futures returns by the early exercise premium and other forecasters for different horizons. This table is similar to Table 3 above with the exception that the dependent variable is the return of FTSE 100 futures contracts rather than the index itself. DY_t is the one-month moving average of the dividend yield. EEP_t^{Call} is the early exercise premium of call options. R_t^{fut} is the FTSE 100 return of the futures contract (lagged). Var_t is the implied variance of the closest to the money European call option. Rf_t is the one-month stochastically detrended risk free rate. ΔVlm is the change in share volume (in million shares). The t-statistics in parentheses are corrected for hetroskedasticity and autocorrelation. Panel A compares the predictive regression of the next day's index excess returns under different specifications. Panel B examines the return predictability at longer horizons of up to two weeks using all the predictors (most exhaustive specification from Panel A). The numbers in the square brackets indicate the number of days the returns leading all the explanatory variables. For example, the column labeled $[2, 3]$ shows the regression of $R_{t+2,t+3}$ on all the explanatory variables at time t.

Panel A: Returns of the Index Futures

DY_t	1.972	1.777	1.768	1.819	2.032
	(0.543)	(0.493)	(0.488)	(0.504)	(0.563)
$\mathbf{EEP}_t^{Call}$		0.043	0.043	0.043	0.043
		(2.659)	(2.623)	(2.663)	(2.679)
R_t^{fut}			-0.013	-0.012	-0.005
			(-0.363)	(-0.331)	(-0.129)
Var_t				-2.135	-2.205
				(-0.277)	(-0.286)
Rf_t				-10.175	-8.431
				(-0.550)	(-0.455)
ΔVlm_t					-0.644
					(-2.385)
R^2	0.000	0.008	0.008	0.008	0.013

Panel B: Longer Horizons

	[1, 2]	[2, 3]	[3, 4]	[4, 5]	[6, 10]
DY_t	1.701	1.274	-3.080	-1.989	0.910
	(0.490)	(0.354)	(-0.853)	(-0.583)	(0.450)
$\mathbf{EEP}_t^{Call}$	0.036	0.017	0.010	0.025	0.009
	(2.379)	(1.099)	(0.585)	(1.516)	(1.050)
R_t^{fut}	-0.016	-0.035	-0.005	0.024	-0.038
	(-0.429)	(-0.965)	(-0.140)	(0.676)	(-2.474)
Var_t	-2.025	1.377	5.480	10.206	4.901
	(-0.215)	(0.156)	(0.624)	(1.097)	(0.811)
Rf_t	-14.135	-5.043	-1.478	7.417	-6.021
	(-0.781)	(-0.288)	(-0.081)	(0.412)	(-0.549)
ΔVlm_t	0.329	0.260	0.391	-0.021	-0.111
	(0.950)	(1.018)	(1.661)	(-0.074)	(-1.156)
R^2	0.008	0.003	0.004	0.005	0.015

Table 5: VAR Results

The table contains the vector autoregression (VAR) estimates of A in $z_{t+1} = Az_t + w_{t+1}$ where the vector z_t is demeaned and is defined as $z_t = [R_t, DY_t, Var_t, Rf_t, \Delta Vlm_t]'$. R_t is the FTSE 100 index excess return. DY_t is the one-month moving average of the dividend yield. Var_t is the implied variance of the closest to the money European call option. Rf_t is the one-month stochastically detrended risk free rate. ΔVlm_t is the change in share volume in million. The order of the VAR was chosen with sequential pretesting. The t-statistics in parentheses are corrected for hetroskedasticity and autocorrelation.

	R_{t+1}	DY_{t+1}	Var_{t+1}	Rf_{t+1}	ΔVlm_{t+1}
R_t	0.071	-0.0001	4.832×10^{-5}	-3.805×10^{-6}	0.003
	(1.341)	(-0.316)	(0.167)	(-0.102)	(0.688)
DY_t	0.536	0.907	0.007	-0.001	0.713
	(0.176)	(51.877)	(0.681)	(-0.172)	(2.041)
Var_t	5.512	0.035	0.708	-0.012	-1.989
	(0.781)	(0.892)	(14.852)	(-1.477)	(-2.812)
Rf_t	-1.306	0.061	-0.206	0.965	-0.089
	(-0.082)	(0.823)	(-1.522)	(48.303)	(-0.073)
ΔVlm_t	-0.506	-0.001	-0.002	-0.0003	-0.102
	(-2.210)	(-1.482)	(-2.791)	-0.897	(-3.683)
R^2	0.010	0.824	0.555	0.877	0.020

Table 6: Identifying the Source of the Forecastability

This table reports the regressions of different components of returns on the *EEP*. $\hat{E}_t(R_{t+1})$ is the fitted value from the VAR regression. $\hat{\eta}_{R,t+1}$ represents news about future excess returns. $\hat{\eta}_{d,t+1}$ represents news about cash flow. $\hat{\eta}_{Rf,t+1}$ represents news about risk-free rate. All these four components are regressed on the call option *EEP* at time t. The t-statistics in parentheses are corrected for hetroskedasticity and serial correlation.

Sample Period		$\hat{w}^R_{t+1}$			$\hat{E}_t(R_{t+1})$
		$\hat{\eta}_{d,t+1}$	$\hat{\eta}_{R,t+1}$	$\hat{\eta}_{Rf,t+1}$	
6/1/92 to 1/12/96		0.040	-0.000	0.001	-0.003
		(2.642)	(-0.394)	(0.460)	(-1.714)
	R^2	0.007	0.000	0.000	0.005
6/1/92 to 7/18/94		0.058	0.001	0.02	-0.004
		(1.752)	(0.730)	(0.879)	(-1.232)
	R^2	0.005	0.000	0.001	0.004
7/19/94 to 1/12/96		0.058	-0.000	0.012	-0.001
		(2.376)	(-1.564)	(1.793)	(-0.734)
	R^2	0.016	0.005	0.004	0.002

Table 7: Dividend Growth Forecast: MIDAS Regression

This table shows results for the following mixed-data sampling (MIDAS) of the bi-weekly dividend growth rate (DG_t) on its own lags and lags of daily call $EEPs$. $DG_t = \alpha + \phi(L)DG_{t-1} + \gamma \sum_{k=1}^{K} \beta(k, \theta) EEP_{t-k/14} + e_t$. Details about the MIDAS regression are in the text. The t-statistics are in parentheses. The F-statistic tests the MIDAS model against the benchmark model in column 1 under the null hypothesis that lagged call EEPs do not forecast the dividend growth rate. The F-statistic is shown and its p-value is in parentheses.

DG_{t-1}	-0.286	-0.289
	(-3.019)	(-3.056)
DG_{t-2}	-0.534	-0.540
	(-4.886)	(-4.942)
DG_{t-3}	-0.606	-0.617
	(-6.877)	(-6.995)
γ		3.093
		(21.525)
θ_1		289.014
		(1.385)
θ_2		500.000
		(1.406)
R^2	0.297	0.326
F		4.766
		(0.004)
Sample Size	116	116

Table 8: Predictive Regression in Subsamples

This table reports predictive regressions of excess futures returns by the early exercise premium and other forecasters for different sub-sample periods. In Panel A, the forecasted variable is the index excess return, whereas in Panel B, it is the index futures contract return. DY_t is the one-month moving average of the dividend yield. EEP_t^{Call} is the early exercise premium of call options. Var_t is the implied variance of the closest to the money European call option. Rf_t is the one-month stochastic detrended risk free rate. ΔVlm is the change in share volume in million. The first column shows the whole sample period and the next two columns display the result for the two sub-samples. The choice of the sub-samples is explained in the text. The t-statistics in parentheses are corrected for hetroskedasticity and autocorrelation.

Panel A: Index Excess Return

Sample period	6/1/92 to 1/12/96	6/1/92 to 7/18/94	7/19/94 to 1/12/96
DY_t	0.490	-1.350	1.480
	(0.163)	(-0.294)	(0.349)
$\mathbf{EEP}_t^{Call}$	0.036	0.038	0.048
	(2.890)	(2.117)	(2.118)
R_t	0.078	0.107	0.020
	(1.476)	(1.489)	(0.359)
Var_t	5.716	6.646	11.849
	(0.827)	(0.742)	(0.892)
Rf_t	-3.630	5.273	-32.259
	(-0.229)	(0.221)	(-0.703)
ΔVlm_t	-0.512	-0.898	-0.042
	(-2.239)	(-3.085)	(-0.130)
R^2	0.018	0.022	0.016
Sample Size	894	528	376

Panel B: Index Futures Return

Sample period	6/1/92 to 1/12/96	6/1/92 to 7/18/94	7/19/94 to 1/12/96
DY_t	2.032	1.336	2.924
	(0.563)	(0.245)	(0.574)
$\mathbf{EEP}_t^{Call}$	0.043	0.041	0.056
	(2.679)	(2.026)	(1.903)
R_t^{fut}	-0.005	0.028	-0.059
	(-0.129)	(0.582)	(-1.039)
Var_t	-2.205	-3.866	4.643
	(-0.286)	(-0.415)	(0.288)
Rf_t	-8.431	-7.553	-9.087
	(-0.455)	(-0.293)	(-0.161)
ΔVlm_t	-0.644	-1.051	-0.0148
	(-2.385)	(-3.158)	(-0.364)
R^2	0.013	0.017	0.016
Sample Size	894	528	376

Table 9: Robustness Check: Put Results

This table reports the predictive regression of return using the put *EEP* (instead of call *EEP*). The dependent variable is the excess return of the FTSE 100 index. DY_t is the one-month moving average of the dividend yield. EEP_t^{Put} is the early exercise premium of put options. R_t is the (lagged) FTSE 100 index excess return. Var_t is the implied variance of the closest to the money European call option. Rf_t is the one-month stochastically detrended risk free rate. ΔVlm is the change in share volume in million. The first column shows the whole sample period and the next two columns show the result for two sub-samples. The t-statistics in parentheses are corrected for hetroskedasticity and autocorrelation.

Sample period	6/1/92 to 1/12/96	6/1/92 to 7/18/94	7/19/94 to 1/12/96
DY_t	1.813	0.452	1.668
	(0.614)	(0.102)	(0.400)
$\mathbf{EEP}_t^{Put}$	-0.007	-0.008	-0.006
	(-0.926)	(-0.939)	(-0.440)
R_t	0.063	0.085	0.020
	(1.276)	(1.285)	(0.365)
Var_t	10.870	12.771	12.301
	(0.949)	(1.020)	(0.411)
Rf_t	-2.312	-0.008	-33.606
	(-0.120)	(0.000)	(-0.722)
ΔVlm_t	-0.474	-0.798	-0.069
	(-2.081)	(-2.751)	(-0.216)
R^2	0.012	0.020	0.004
Sample Size	894	528	376

Table 10: Predictive Regression under Alternative *EEP* Aggregation

This table presents the predictive regression of the future return under alternative *EEP* aggregation methods. The dependent variables are the excess return of the FTSE 100 index. DY_t is the one-month moving average of dividend yield. EEP_t^{Mat} is the early exercise premium of call options aggregated daily by interpolating both moneyness and time to maturity. EEP_t^{Avg} is the early exercise premium of call options aggregated daily by averaging the *EEP* of all contracts. R_t is the FTSE 100 index excess return. Var_t is the implied variance of the closest to the money European call option. Rf_t is the one-month stochastic detrended risk free rate. ΔVlm is the change in share volume in million. The first column shows the whole sample period and the next two columns show the result for the two halves of the sample. The t-statistics in the parentheses are corrected for hetroskedasticity and autocorrelations.

Panel A: *EEP* Controlled for Maturity

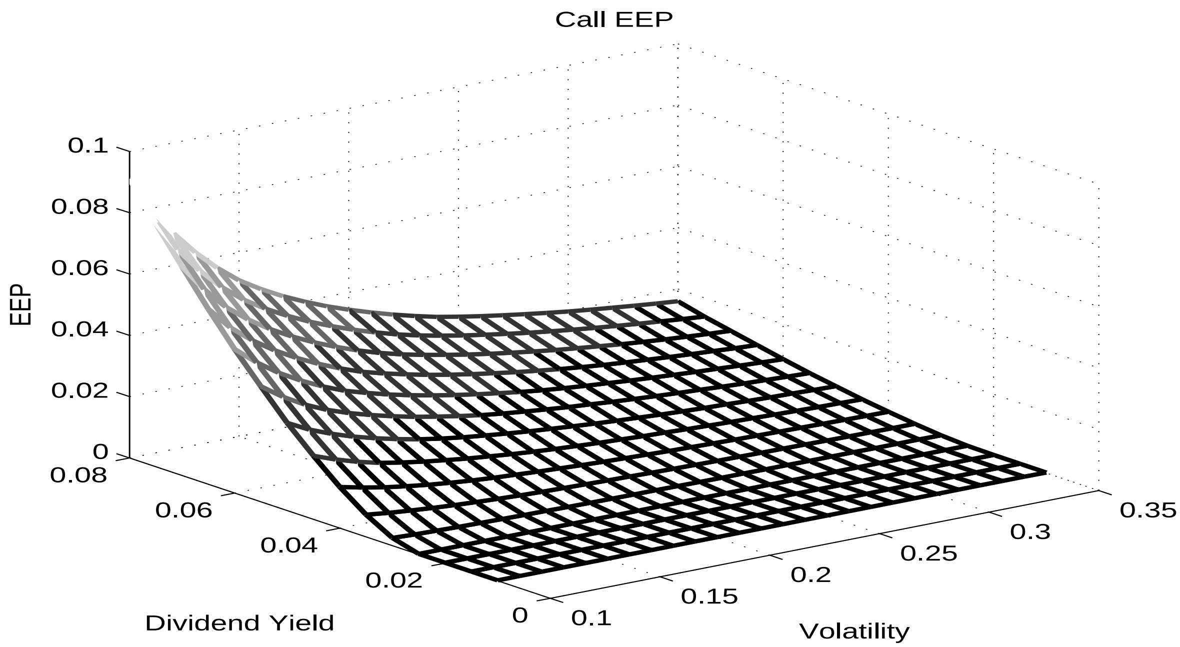
Sample period	6/1/92 to 1/12/96	6/1/92 to 7/18/94	7/19/94 to 1/12/96
DY_t	0.877	-0.945	1.761
	(0.291)	(-0.204)	(0.410)
$\mathbf{EEP}_t^{Mat}$	0.026	0.029	0.036
	(2.529)	(2.300)	(2.008)
R_t	0.079	0.109	0.017
	(1.485)	(1.515)	(0.325)
Var_t	4.767	6.374	11.322
	(0.687)	(0.703)	(0.967)
Rf_t	-4.717	5.150	-25.770
	(-0.262)	(0.216)	(-0.553)
ΔVlm_t	-0.508	-0.916	-0.161
	(-2.198)	(-3.148)	(-0.457)
R^2	0.015	0.026	0.014
Sample Size	894	528	376

Panel B: Average *EEP*

Sample period	6/1/92 to 1/12/96	6/1/92 to 7/18/94	7/19/94 to 1/12/96
DY_t	-0.327	-1.463	-0.189
	(-0.109)	(-0.319)	(-0.044)
$\mathbf{EEP}_t^{Avg}$	0.042	0.046	0.045
	(3.115)	(2.469)	(1.976)
R_t	0.087	0.122	0.024
	(1.638)	(1.668)	(0.422)
Var_t	5.183	5.495	10.323
	(0.752)	(0.621)	(0.784)
Rf_t	-4.405	4.925	-31.313
	(-0.279)	(0.208)	(-0.684)
ΔVlm_t	-0.505	-0.904	-0.023
	(-2.187)	(-3.078)	(-0.072)
R^2	0.019	0.029	0.014
Sample Size	894	528	376

Figure 1: Variation in the level of the *EEP*

The two graphs display the magnitudes of the call and put *EEP*s computed using numerical valuations of an at-the-money, one-month American option contracts. The risk free rate is 8%. The top (bottom) graph displays for the call (put) *EEP* for various levels of the dividend yield and volatility.



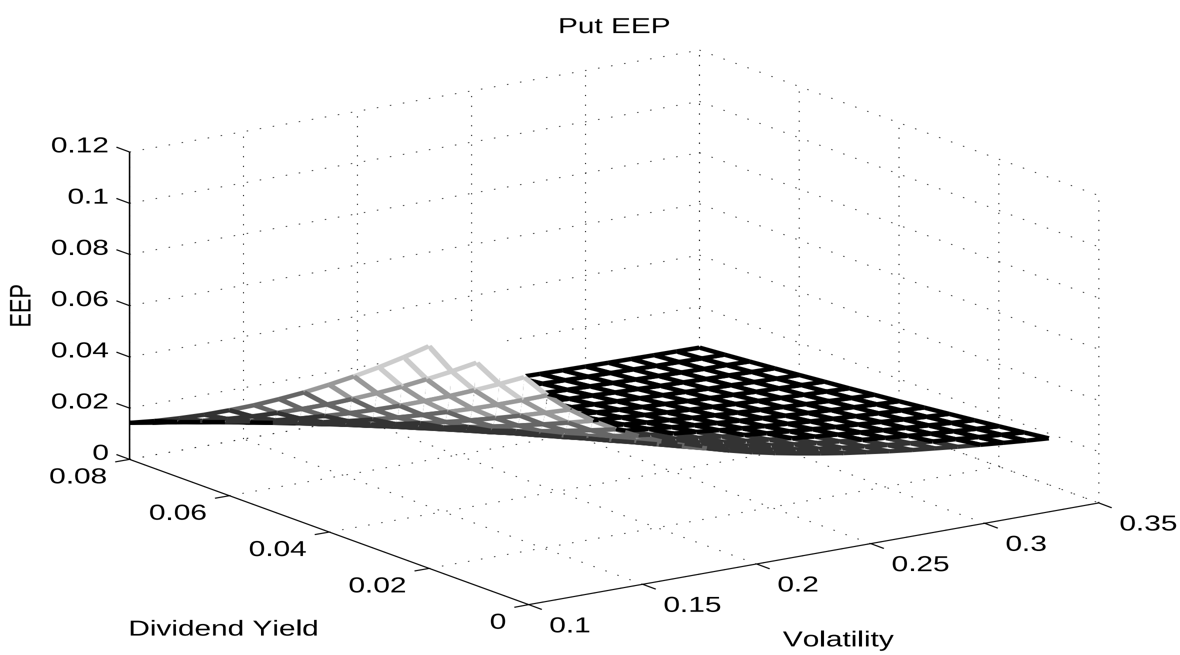


Figure 2: MIDAS Weights

This graph pictures the shape of the β coefficients against the lagged days in the following mixed-data sampling (MIDAS) regression, $DG_t = \alpha + \phi(L)DG_{t-1} + \gamma \sum_{k=1}^{K} \beta(k,\theta)EEP_{t-k/14} + e_t$. Dividend payments for the FTSE 100 index stocks are announced between 10 to 15 days before the ex-dividend date. The shaded pattern denotes that period. The daily EEPs contain information about future dividends 2 to 3 weeks before the ex-dividend date, right before the announcement of the dividend payments.