Three Hundred Years of Monthly Return Predictability: A Comprehensive Examination and Transfer Learning †

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Abstract

I construct a 300-year monthly testing sample for the UK market and study the return predictability in both the UK and the US. I conduct out-of-sample tests with 312 prediction setups based on 23 popular predictors, 3 model updating windows, and 3 common forecast combinations. Over the long run, the predictability declines substantially. Only 12 setups show out-of-sample R-Squared greater than 0.01 in the UK, while 19 setups have out-of-sample R-Squared greater than 0.01 in the US. 23 setups lead to positive but limited economic gains in the UK. However, most setups realize sizable economic gains in the US. Transfer learning setups that fit models using UK data show substantially stronger performance in the US market, compared to fitting models using US data. The predictability shows tremendous fluctuation in the short term, which urges caution in interpreting out-of-sample tests. The short-term fluctuation of predictability can easily lead to disagreements in testing results due to the change of sample coverage. With the UK history, I show that the predictability concentrates in interaction periods between GDP turning points and extreme return months. The predictability also concentrates in rare events, such as epidemic years. On average, the predictability is the weakest in summer and the strongest in winter and spring.

Key Words: Certainty Equivalent Return, Out-of-sample R^2, Rare Events, Return Predictability, Transfer Learning

JEL classification: C22, C53, G11, G12, G17, N2

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1 Introduction

Many studies examine the out-of-sample (OOS) return predictability (Campbell and Thompson 2008, Goyal and Welch 2008, Rapach and Zhou 2021, etc.) in the monthly data. But the common setups are often established based on a US sample going back to 1926 or 1945. However, the history of modern equity market started from the beginning of the 1600s. In the 18th century, the UK market was already active. By the 19th century, the UK market included hundreds of firms (Acheson et al. 2009, Campbell et al. 2021, etc.). Thus, the mainstream predictability studies only reflect about one-fourth of the financial market 's history.

To fill this gap in the literature, I construct a 300-year monthly testing sample and provide a comprehensive examination of the OOS predictability in the UK and the US markets. To the best of my knowledge, my sample is the longest in the literature of monthly return predictability. My data for the UK market go back to May 1710, right after the birth of the Kingdom of Great Britain and the extended US data go back to February 1857, before the American Civil War.

I include 25 popular predictors with 3 different model-updating windows over 2 samples for each of the markets, along with 3 different combination methods applied to different groups of predictors (Goyal and Welch 2008, Rapach et al. 2011, Neely et al. 2014, Rapach and Zhou 2021). In total, I test the UK market with 108 prediction setups, including the 300-year predictions by dividend yield and dividend price, and I test the US market with 102 prediction setups.

The purpose of this paper is not to advocate any prediction setups nor to survey predictors or methods. Simply, with the long history in my data and the simultaneous observation of the two most important markets in the past three centuries, I seek to understand whether the common setups can lead to monthly predictability over the super long run and how the predictability changes through time and across the border.

The OOS tests confirm the predictability over 300 years in the UK, although the predictability only shows up in a very limited group of setups. Despite being significant overall in the longer history, the top performing setups gradually lost their power in the past 100-200 years, implying that the loss of predictability happens along the history and does not need to come from new publication about the predictors (McLean and Pontiff 2016). Actually, the rolling OOS R^2's show that the predictability of top performers declines from a peak level of above 10% to today's level just below 1%. At the same time, predictability carries tremendous short-term fluctuations. This means that even past equity premium, can still make meaningful predictions in a very short window every once in a while and and the predictability can disappear completely very quick. This urges caution in our interpretation of OOS predictability documented in the literature, since even a very short difference in sample coverage can lead to completely different conclusion, provided that the overall OOS predictability is so close to zero while the fluctuations, measured with standard deviations of 5-year rolling window OOS R^2s, are of multiple folds of the overall OOS predictability (Goyal et al. 2021).

The biggest recent drop for the UK happened in the late 19th century, a time point coinciding with the substantial reduction of information delay because of the rollout of domestic and transatlantic telegraph cables (Hoag 2006, Steinwender 2018, Wache 2021).

Figure 1 shows the decline in predictability overall with the top performers for the UK and the US markets based on expanding window OOS R^2. Figure 2 shows the short-term predictability fluctuations based on rolling 5-year window OOS R^2. Beyond the decline of the predictability, observing Figure 1 and Figure 2, we can quickly understand the importance of having a long history for the predictability tests, i.e., focusing on different subperiods can easily lead to different conclusions about the predictability because of the strong short-term fluctuations, even if the time window is not so "short".

Although the predictability declines substantially, a few prediction setups, such as the univariate regression with ltr for the UK market and several combination forecast predictions for the US market, are surprisingly consistently delivering statistically meaningful OOS predictability across the longest sample available, the past 50 years and recent 5 years. However, the dividend variables are not among these top performers. Contrary to the findings from Golez and Koudijs (2018) with the annual data spliced with series from 3 countries, dividend variables are barely effective in any of the long samples at the monthly frequency. However, dividend yield and dividend price are stronger in the last 50 years of the UK sample delivering annualized OOS R^2s of 2% and 0.9%, respectively.

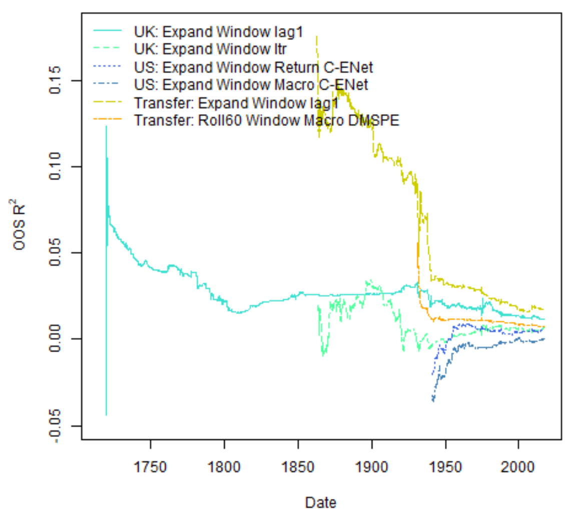

Figure 1: Expanding Window Best Performers by OOS R^2

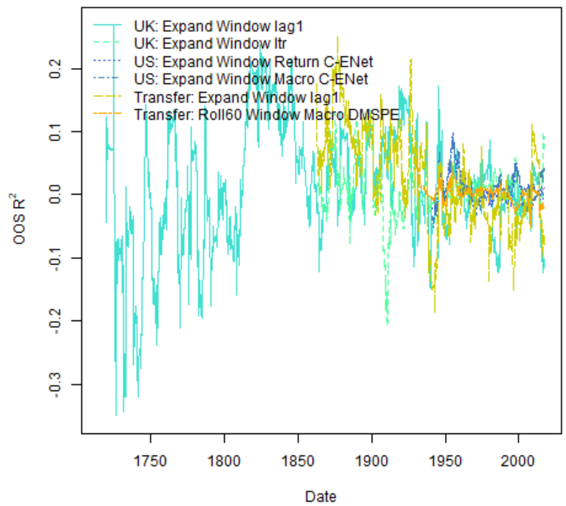

Figure 2: 5-Year Rolling Window Best Performers by OOS R^2

Additionally, only 23 prediction setups deliver positive economic gains measured with certainty equivalent return (CER) (Campbell and Thompson 2008, Goyal and Welch 2008, Rapach et al. 2011) in the UK. Interestingly, despite the similarity in the OOS statistical tests based on OOS R^2, most of the prediction setups lead to positive CER gains in the US. Meanwhile, the literature seems to show correlation between OOS predictability and CER gains. However, the statistical performance and the economic gains do not seem correlated with a one-to-one relation.

In the UK, the best performing setups are the expanding window updating linear regressions relying on lag1 equity premium and the return on long-term government bond in the UK, while the best performing setups for economic gains are all rolling window combination methods based on Discount Mean Squared Prediction Error (DMSPE) (See Rapach et al. 2011). It is also common that even if a setup does not show significant statistical predictability, they can often lead to sizable CER gains.

In the US market, the best statistical performers are combination setups for both samples, while the top earners of economic gains are univariate regression setups. The univariate predictor setups, such as the prediction with lag1 equity premium, suffer enormous transaction costs in both the UK and the US markets. There is no significant domination in the performance attributable to the updating windows.

Related, only limited studies have documented the transferable predictability across the border. Rapach et al. (2013) are the pioneers in the exploration of market information cross border for predictability. They examined the lead-lag predictability in the non-US industrialized markets using the US market returns. They report that the non-US returns display a limited predictive ability to the US returns. Jiang et al. (2020) are the first to apply a stock level image model to predict international stocks based on parameters trained with the US data from 1993 to 2019. They document that over their sample period, the model performance internationally is as good as the performance in the US data.

Questions arise naturally with these studies. First, are the findings from Rapach et al. (2013) generalizable to a conclusion that the non-US market information is limited in predicting the US market? Second, if returns from one market can predict returns from another market and the charting techniques picked up by the image model can make predictions in the international markets, is it possible that the common successful market predictors in one country can also lead to predictive power in another country in the long run? To answer these questions, I include another 98 transfer learning setups that use the UK data to model the equity premium and apply the trained models to the US data in OOS tests.

One has to be careful in the transfer learning settings. If a study trains models in one market and tests the predictions in another market while the time windows overlap, the OOS tests could suffer from forward-looking data leak, making the conclusion even more vulnerable. Because the UK data has a longer history, fitting models using the UK history is possible such that no forward-looking data leak can happen for the OOS tests using the US data in one period ahead.

In my transfer learning setups, most of the models trained and updated using UK data deliver significant economic gains in the US market, implying the possibility of learning market experience from the UK and applying it to the US market. For the OOS statistical tests, the expanding window models relying on the long UK history achieve higher predictability, especially in the early part of the sample. The top performers include both technical indicators and macroeconomic predictors.

The expanding window setups show dominating predictive power in the OOS tests for the transfer learning setups in the longer sample. The transfer learning models also deliver economic gains that in general are larger than those from the models trained with the US data. These findings emphasize the importance of adding more data in the search for OOS performance.

Given the data, I leverage the long history to investigate the important economic and historical moments. Many studies show that the OOS predictability concentrates in recessions, namely negative GDP growth periods. (Rapach et al. 2011, Cujean and Hasler 2017). My results show that the predictability is not simply concentrating in the negative GDP growth periods. It concentrates in the deeply negative GDP growth periods, the GDP turning points, and specific interaction periods between the macroeconomy and the stock markets. The predictability is the strongest during the negative (positive) extreme return months when GDP is also turning negative (positive).

Rare events could also be a factor for higher predictability, since the expected equity premium can change with rare event probabilities (Barro 2009). Focusing on the UK, I collect a list of rare events and document the predictability conditional on rare events, including population losses, epidemics and pandemics, and wars.

Note that the rare events do interact with GDP changes, but they do not fully overlap. The Cramer 's V between rare events and decreasing GDP is only 0.07, showing a weak categorical variable correlation. Predictability is strongly conditional on epidemic years, pandemic years, and famine years. Despite the tremendous impact of WWI and WWII, in the long run, we earn only limited predictability during the major wars comparing to the predictability earned during years with famine and diseases. Conditional on calendar months, both UK and US tests show the concentration of predictability in colder months, and the worst months are all in the summer.

This paper makes several contributions to the return predictability literature. First, I put together a real long-run testing sample and provide a comprehensive examination of predictability over the super long run with a variety of common setups. Second, I investigate the predictability in the UK and the US markets simultaneously and conduct a full scale transfer learning test to show the possible transferability of the predictability. Third, I explore the economic history and link the predictability across the different historical moments to analyze the concentration of the predictability.

This paper is closely related to a long list of studies in the mainstream return predictability literature that focuses on the macro-level information and the technical indicators (Neely et al. 2014, Rapach et al. 2011, Cochrane 2008, Goyal and Welch 2008, Goyal and Welch 2003, Lettau and Ludvigson 2001, Kothari and Shanken 1997, Kandel and Stambaugh 1996, Fama and French 1988, Keim and Stambaugh 1986, etc.). However, due to limited data availability, no study has investigated the monthly return predictability over the super long run in a relatively comprehensive way.

Golez and Koudijs (2018) are by far the closest and they are the pioneers in adopting results from economic history to modern predictability study. But they limited their focus on the dividend yield. There are countless studies that support the focus on the dividend-related variables (Campbell 1987, Fama and French 1988, Cochrane 2008, Pástor and Stambaugh 2009). However, a broader set of variables are left, ex, technical indicators and interest rates (Neely et al. 2014, Keim and Stambaugh 1986, Campbell 1987 and Fama and French 1989). In my setup, I construct monthly data more than 3720 months and I investigate the predictability over the entire set of common predictors with meaningful availability in the super long run.

Golez and Koudijs (2018) also relied on the data from Acheson et al. (2009). However, instead of using prevailing capitalization, Acheson et al. (2009) used the concurrent month capitalization to calculate the index, which can lead to unnecessary loss of accuracy in all the statistical tests (Campbell et al. 2021).

In the end, Golez and Koudijs (2018) limit their focus on annual data combined across three countries with about 400 data points. This setup is not so close to today 's popular strategies that focus on monthly observations of a continuing domestic equity market (Lettau and Ludvigson 2001, Goyal and Welch 2008, Dong et al. 2020, etc.). It is also known that the longer horizon can make the predictability easier to realize statistically and the predictability is actually proportional to the prediction horizon (Boudoukh et al. 2008, Cochrane 2008, Barberis 2000, Campbell and Shiller 1988b, Campbell and Shiller 1988a). With such annual data, the volatility of predictability gets blurry. Overall, before my paper, we do not have a good reference to understand the predictability with a monthly rebalance strategy applied to a natural domestic equity market.

This paper is also related to the study of Jiang et al. (2020) who apply transfer learning with an image model trained on the US data to predict foreign markets' stock returns. Their study is different from this paper in two ways. First, this paper is a traditional return predictability paper and I focus on a set of common predictors and setups instead of a single machine learning model. The most sophisticated model in my setup is probably just the constraint elastic net used for forecast combination (Hastie et al. 2009, Rapach and Zhou 2021, Bates and Granger 1969, Granger and Ramanathan 1984).

Second, this paper examines the return predictability with a long history and does not relate to the stock level predictability in any situation. The purpose is to examine the predictability of the market at a larger scale with common setups such that we can learn about how the predictability generally evolves in the long run.

The paper proceeds as follows. Section 2 describes the data, presents summary statistics, and reviews empirical methods. I report OOS test results in Section 3 and 4. Section 5 discusses the short-term volatility of predictability. Section 6 and 7 explore critical moments when predictability is high. The paper concludes in Section 8.

2 Data and Econometric Methods

In this section, I provide a brief description of the data sources and how I constructed the testing samples. The major source of the UK data is the Bank of England and the NBER macrohistory database. The Bank of England launched an effort several years ago named "A Millennium of Macroeconomic Data For The UK", which centralizes the data sets from economic history (Thomas and Dimsdale 2017). I rely on the Bank of England for UK 's macroeconomic variables through the time window covered in my sample and I take variables such as short-term rates, consol yields, corporate bond rates, inflation.

I also rely on the Bank of England data for the UK index series before 1830, when the data of Campbell et al. (2021) started, and after 1928, when Actuaries's Investment Index, the former index of today 's Financial Times Stock Exchange All Share, launched. Note that the data from Acheson et al. (2009) formed the index based on concurrent market capitalization and thus can mislead the tests for the specific period.

The major source of the US data is from Goyal and Welch (2008), with supplements from NBER macroeconomic history database and Robert Shiller 's website (Shiller 1989). Goyal and Welch (2008) include the treasury bill rates and corporate bond yields, etc., and I get supplements from NBER for New York commercial papers and the railroad stock index in 185701:186912. Robert Shiller 's website maintains the estimated Standard and Poor 's composite index going back to 1870.

2.1 The UK Data, the Proxies and Their Influence

For the UK market, the Bank of England centralized a selection of historical market time series from a variety of raw data sources. The Bank of England then combines them into a long return series and

I adopt the series as the main approximation of the market returns.

Specifically, the Bank of England calculates the market returns based on the share prices of the British East India Company, the Bank of England and South Sea Company from May 1710 to January 1811. Then, the Bank of England calculates a return series with 63 firms, excluding mines and weighted by paid-up capital, from February 1811 to February 1825.

The Bank of England uses several UK series from the NBER macrohistory database after 1871 for several decades. Specifically, from 1871 to 1914, the market return is based on 25-82 securities. Then, the market return is from the industrial share prices published in Banker 's Magazine until November 1921. Banker 's Magazine introduced an index covering 278 variable dividend securities in the following month, and the Bank of England adopted this index for the market return until December 1928.

From January 1929, the market return is from Actuaries's Investment Index of Ordinary Industrial Shares published in Monthly Digest of Statistics until the official introduction of today 's Financial Times Stock Exchange All Share Index in April 1962. For the period between January 1830 and December 1928, the market return is from Campbell et al. (2021). Campbell et al. (2021) undertook the cost to digitize the Investor Monthly Manual from the International Center of Finance at Yale University, along with supplements. During WWI, five data points are missing, related to the close of the London Stock Exchange and I linearly interpolate these 5 data points.

Because of the long history, I must make necessary yet conservative approximations for missing information, mainly though the use of proxies. For example, the UK did not have a liquid treasury bill market during the 18th-19th century, so we cannot directly apply the Bank of England 's official short-term rate to the calculation of equity premium. Golez and Koudijs (2018) used the return rate on console to approximate the treasury bill. However, since the consol returns are often deeply negative and very volatile at the monthly level, applying consol returns to the calculation of equity premium can lead to unnecessary changes in the statistical moments because treasury bills are rarely negative nor seldomly volatile.

Acheson et al. (2009) suggested the use of inflation rates, and Goyal and Welch (2008) used regression with commercial paper. I synthesize their ways and use both inflation and commercial paper to approximate the UK treasury bill for 171005:171802 and 171802:191912.

When I have to adopt approximation for a series, my approximation is conservative and precise. I do not approximate any series if there exists a proper proxy. For example, I approximate the treasury bill using regression with consumer price index inflation for 171005:171803 (Acheson et al. 2009, Goetzmann and Ibbotson 2006) and I adopt the short-term bill from the East India Company as a proxy for the treasury bill from 1718. East India Company 's short-term bond is good for two reasons. First, the company is government-chartered. Second, this short-term rate is the only documented short-term rate besides the official bank rate.

Following this period, I adopt the short-term prime bill to proxy the treasury bill rate until 1923, when Caple and Webber 's treasury bill rate became available. The short-term prime bill is a bill accepted as first-class credit. The rate is consistently lower than the official short-term rate before 1923, showing a closer relationship with the true risk-free return. Since the prime bill is still often lower than the treasury bill rates taken from Caple and Webber 's data after 1923, I take the minimum between the prime bill and the UK treasury bill as the treasury bill in my sample for the UK from 1923 to 1974. After 1975, the Bank of England started recording the treasury bill rate on its own and I use the rate from the Bank of England directly.

Along with the treasury bill, the equity premium needs to be dividend-adjusted. However, conventional documentation of market returns in the early days is often dividend-exclusive. To get a proper proxy of the equity premium for the UK market before the data from Campbell et al. (2021), I obtain the actual dividend records from the Bank of England and apply the dividend records as proxy for the period 171005:182912.

Neither of my approximations or proxies above affects the OOS statistical tests, since the difficulty of OOS predictability comes from the variation representing the incorporation of new information and uncertainty. Empirically, both dividend yield and treasury bill are positive, with very limited variations. At most, the approximations and proxies can only move the mean of the final equity premium proxy, leading to a more realistic interpretation of economic gains. Overall, the equity premium for the UK in three centuries is just around 2% annually, consistent with the literature (Golez and Koudijs 2018).

To ensure that the proxies of dividend and treasury bill do not drive the OOS test results, I produced two unreported full sets of results, where I tested against the raw series. The first set of results is based on raw series with direct use of the official short-term rate from the Bank of England and no dividend proxy adjusted return, while the second set of results is based on raw series with treasury bill proxies but also no no dividend proxy adjusted return. There is no change in the statistical tests and limited OOS predictability does exist in the UK over the entire sample.

2.2 Variable Definition

Because of the inevitable limitations of including such a long history in the analysis, I have to be strategic on what I can include for a full-size monthly test. I form two setups for each of the two markets to accommodate the time-varying availability of important predictors. The two samples of the UK span the periods 171005:201612 and 185401:201612. Only the second sample includes macroeconomic predictors other than dividend yield and dividend price. Similarly, the US samples span the periods 185701:202012 and 192601:202012. The first US sample does not include dividend yield nor dividend price. Only the second US sample includes macroeconomic predictors. For both the UK and the US markets, the beginning of the second sample is the time when all the macroeconomic variables became available.

I end up with a selection of common predictors. For the super long run, I mainly rely on the so-called technical indicators from Neely et al. (2014). However, with the dividend yield and the dividend price proxies based on the Bank of England dividend record, I managed to include a long run monthly test on the dividend predictor. There are many reasons for us to do this. For example, Campbell-Shiller decomposition Campbell and Shiller (1988b) tell us that the expected returns are directly related to the dividend and the price. I supplement the technical indicators with the source variables such that I can better understand the drivers of the predictability demonstrated with the technical indicators, if they do demonstrate predictability in the long run.

I focus on the macroeconomic predictors with the relatively shorter samples for both markets. I also include the common forecast combination methods, such as C-ENet (Neely et al. 2014, Rapach and Zhou 2020, Rapach and Zhou 2021). To better understand how dynamic the relation between the predictors and the equity premium is, I also include different rolling window schemes for model updates. I list out the variables and the forecast combinations included in my tests below. The variables are all in decimals, except dividend yield, dividend price and equity premium, which are converted to decimals first and then converted to log scales.

Equity Premium (in log): I define Equity Premium as the difference between log scale market return with dividend and log scale risk-free rate. I calculate the risk-free rate as treasury bill rates divided by 12 in both the UK and the US markets. For the UK, the market return is the spliced time series from the Bank of England, data from Campbell et al. (2021) and the FTSE historical series obtained from Ryland Thomas. Equity Premium is the target of all prediction tests in this paper. All variables below are the predictors.

$MA_{1,9}$: $MA_{1,9}$ is an indicator with a value based on the comparison between the lag1 equity premium and the 12-month moving average. The indicator has a value of 1 if the short-term moving average is greater than the long-term moving average, and 0 otherwise.

$MA_{2,9}$: Similarly, $MA_{2,9}$ is an indicator with a value based on the comparison between the 2-month moving average of equity premium and the 12-month moving average of the equity premium. The indicator has a value of 1 if the short-term moving average is greater than the long-term moving average, and 0 otherwise.

$MA_{3,9}$: $MA_{3,9}$ is an indicator with a value based on the comparison between the 3-month moving average of equity premium and the 12-month moving average of the equity premium. The indicator has a value of 1 if the short-term moving average is greater than the long-term moving average, and 0 otherwise.

$MA_{1,12}$: $MA_{1,12}$ is an indicator with a value based on the comparison between the lag1 equity premium and the 12-month moving average of the equity premium. The indicator has a value of 1 if the short-term moving average is greater than the long-term moving average, and 0 otherwise.

$MA_{2,12}$: $MA_{2,12}$ is an indicator with a value based on the comparison between the 2-month moving average of equity premium and the 12-month moving average of the equity premium. The indicator has a value of 1 if the short-term moving average is greater than the long-term moving average, and 0 otherwise.

$MA_{3,12}$: $MA_{3,12}$ is an indicator with a value based on the comparison between the 3-month moving average of equity premium and the 12-month moving average of the equity premium. The indicator has a value of 1 if the short-term moving average is greater than the long-term moving average, and 0 otherwise.

$Lag1$: $Lag1$ is the equity premium from last month.

$Lag2$: Similarly, $Lag2$ is the equity premium from 2 months ago.

$Lag3$: $Lag3$ is the equity premium from 3 months ago.

$Mean_9$: $Mean_9$ is the 9-month moving average.

$Mean_{12}$: $Mean_{12}$ is the 12-month moving average.

MOM_9: MOM_9 is an indicator with a value of 1 when the market index is higher in the past month than 9 months earlier.

MOM_{12}: MOM_{12} is an indicator with a value of 1 when the market index is higher in the past month than 12 months earlier.

DY (in log): I define DY as the difference between log dividend and the lagged price. The variable is further lagged to be applied in predictions. The dividend series is from the Bank of England dividend records in the 17th century, Campbell, Grossman and Tuner (2021) who digitize the data from the historical Investor Monthly Manual and FTSE all share history.

DP (in log): DP is the difference between the log dividend and the concurrent price. The variable is also lagged in predictions. The dividend is from the same source as in dividend yield.

TBL: TBL is the treasury bill rate, or the annualized risk-free rate. Because there is no real liquid risk-free rate in the early days and the literature does not directly apply the Bank of England short-term rate for early days, I have to approximate the treasury bill with other short-rates. I use regressions to approximate the UK TBL rates (Goyal and Welch 2008) in the 1710s. Specifically, I regress the treasury bill annual consumer price index through regression from 1923 to 2016 and linearly interpolate the regression estimates to the monthly level from May 1710 to March 1718. From 1718 to 1753, I approximate the UK treasury bill with the yield on short-term bonds of the British East India Company. I approximate the UK treasury bill with short-term prime bills from 1753 to 1923. From 1923 to 1975, the UK treasury bill is the lowest rate between the treasury bill from Caple and Webber and the prime bills. After 1975, when the Bank of England started recording treasury bill rates on its own, I directly take the rate from the Bank of England. In the period of 185701:191912, I follow Goyal and Welch (2008) and adopt the regression estimate as the treasury bill for the UK, using New York Commercial Paper. The regression has an R-square of 98.67%. After 1920, the US data use the documented rates.

LTY: LTY is the long-term bond yield. For the UK, the LTY is the consol yield and LTY for the US is the long-term government bond yield from Amit Goyal 's website.

LTR: LTR is the long-term bond return rate. For the UK, because the consol is perpetual, I calculate the return through the mathematical relation. The LTR for the US is directly from Amit Goyal 's website.

DFY: DFY is the default yield spread. Because of limited availability, the default spread is the spread between consol yield and corporate bond yield in the UK. In the US, it is the spread between investment-grade corporate bonds and junk-grade corporate bonds.

DFR: DFR is the default return spread. Because of limited availability, I approximate the default return spread with the spread between consol return and corporate bond return in the UK. In the US, it is the spread between investment-grade corporate bond return and junk-grade corporate bond return.

$INFL$: $INFL$ is the inflation rate. Because of the data limitation, I adopt the producer price index to calculate year over year inflation on a monthly basis for the UK. In the US, where the consumer price index is available, the inflation is based on the consumer price index and I also calculate it as the year over year changes on a monthly basis.

TMS: TMS is the term spread defined as the difference between consol yield and short-term rate in the UK. The TMS is proxied with the long-term government bond yield and treasury bill rate in the US.

Return_CMean: The mean combination based on the predictions from technical indicators that are derived based on equity premium.

Macro_CMean: The mean combination based on the predictions from macroeconomic predictors.

Mix_CMean: The mean combination based on all predictions.

Return_DMSPE: The discounted mean squared prediction error (DMSPE) combination based on the predictions from technical indicators that are derived based on equity premium.

Macro_DMSPE: The DMSPE combination based on the predictions from macroeconomic predictors.

Mix_DMSPE: The DMSPE combination based on all predictions.

Return_CENet: The elastic net (ENet) combination based on the predictions from technical indicators that are derived based on equity premium.

Macro_CENet: The ENet combination based on the predictions from macroeconomic predictors.

Mix_CENet: The ENet combination based on all predictions.

2.3 Summary Statistics

Table 1 presents the summary statistics in different periods accommodating the different data availability. The equity premium-related predictors, such as lags and means, are in decimal and macroeconomic variables are in percentage. These statistics are all at the monthly frequency.

Table 1 shows that the UK market differs from the US market in the variations. The US market is considerably more volatile. The monthly standard deviation is about 1.5% higher than the UK 's market standard deviation, which adds up to a difference of about 3.675% annually. The US market is also considerably more right-skewed, which means a higher probability of realizing a positive equity premium. The short-term rate seems higher in the UK, probably because of the higher short-term rate in the early years. Overall, both markets show increasing equity premiums from the longer sample to the shorter sample. The US market also has a higher market variation in the more recent shorter sample. In the observable periods, the US market delivers higher equity premium comparing to the UK market. The summary statistics are consistent with the literature (Rapach et al. 2011, Campbell et al. 2021, Golez and Koudijs 2018, Acheson et al. 2009).

[INSERT TABLE 1 HERE]

Figure 3 demonstrates the expanding averages of the equity premium for the UK and US markets. The rolling averages show the short-term co-movements. As shown, the equity premiums in both markets are higher in recent decades.

2.4 Predictive Setups and Forecast Combinations

I attempt to be comprehensive, but not in a way to survey all recent developments of popular methods. Instead, I focus on the classic method, i.e., univariate linear regression, and the selected combination methods, such that I can explore the time-varying nature of the methods and compare the predictability in the two most important markets. I further alternate the combination of the popular univariate

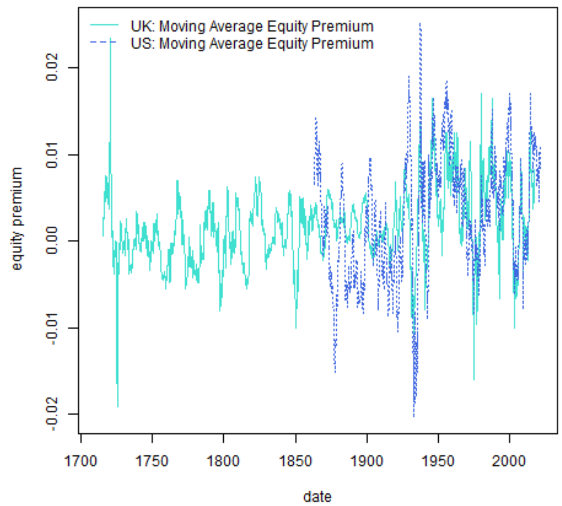

Figure 3: Equity Premium 5-Year Rolling Average

predictors, the models, and three different updating windows, resulting in 312 different prediction setups. Limiting the focus can better serve the purpose of interpreting the findings and make the results presentable.

At each time point, I split the data into the in-sample (IS) training set and the OOS testing set. The model only sees IS observations and makes the OOS predictions using predictors observed before the realization of return in the OOS period. This setup provides an environment that simulates the real world updates of beliefs and is the important setup that all predictability studie should rely on (Martin and Nagel 2021). I slide the window forward to repeat this mechanism to get all the predictions. For the predictions based on univariate regressions, I first construct the IS predictive regression taking the following form,

$$r_{t+1} = \beta_0 + \beta_1 x_t + \varepsilon_{t+1}, \tag{1}$$

where r_{t+1} is the equity risk premium and x_t is the prevailing value of the predictor from past period.

I then document the coefficients and apply the fitted model to the one-period-ahead prediction. Following the literature, I also include the full sample predictive regressions in Table 2 to show the IS relations across the entire sample. However, it is well-known that the IS predictive regressions are likely to overfit the data and lead to incorrect perceptions about predictive power in the real world. Therefore, we have to be cautious when interpreting Table 2. Table 2 shows that, in both UK and US samples, most of the variables are statistically significant in the univariate predictive regressions, but almost all are with small IS R-squares.

I include 3 popular forecast combination methods, i.e., Discounted Mean Squared Prediction Error (DMSPE), Combination Mean (C-Mean), and Combination Elastic Net (C-ENet) (Rapach et al. 2011, Rapach and Zhou 2020, Dong et al. 2020). These methods are popular and widely applied in recent literature and show top performance in the recent US sample.

For DMSPE, I calculate the mean squared error of the past OOS predictions and apply a discount on the error. I repeat this procedure for all predictions and select the minimum error predictors based on the past OOS performance to make the new one-period-ahead predictions. To stay focused, I only consider the discounting factor of 1. The weights are calculated as:

$$\omega_{i,t} = \phi_{i,t}^{-1} / \sum_{j=1}^{N} \phi_{j,t}^{-1}, \tag{2}$$

where

$$\phi_{i,t} = \sum_{s=m}^{t-1} \theta^{t-1-s} (r_{s+1} - \hat{r}_{i,s+1})^2, \tag{3}$$

and θ is the discount factor. Since I apply discount factor of 1, the DMSPE essentially is the combination of Bates and Granger (1969).

The C-Mean and C-ENet are similar in their logic. To get a C-Mean prediction, first, we need a set of predictions from individual prediction setups. Then, we average the predicted values from the individual setups to synthesize a new prediction. C-ENet goes beyond the simple average and applies the popular shrinkage regression with both L1 and L2 regularization to remodel the predicted values against an OOS realization. The ENet takes the form,

$$\min_{\beta_0,\beta_1,\ldots,\beta_n} \left\{ \sum_{t=1} \left(r_{t+1} - \beta_0 - \sum_{i=1}^{n} \beta_i x_{i,t} \right)^2 + \lambda_{i=1}^{n} \left[\frac{1}{2}(1-\alpha)\beta_i^2 + \alpha|\beta_i| \right] \right\}, \tag{4}$$

where α is a hyperparameter that mixes the l_1 and l_2 penalizations. In my C-ENets, I specify $\alpha = \frac{1}{2}$.

After remodeling with observations and predictions from the past, I take the mean of the prediction that is with nonzero coefficients to form the one-period-ahead prediction for the next OOS period.

To ensure consistency with the literature, I apply constraint convex optimization to combine Granger and Ramanathan (1984) regression with ENet (See Hastie et al. 2009, Rapach and Zhou 2021, Dong et al. 2020). Granger and Ramanathan regression for forecast combination requires two constraints, i.e., beta estimates sum up to 1 and all beta estimates are greater than or equal to zero. This is economically meaningful. The successful individual prediction should contribute to the new prediction in positive values. A negative coefficient on a prediction shows that the prediction negatively contributes to the combination prediction. Therefore, we exclude the prediction in the combination.

I reserve 60 (240) months observations for expanding windows and 60-month rolling (240-month) setups at the beginning of each prediction model. I then update them with the associated window schemes. For example, the expanding window will use all observations from history, while the rolling windows will use their associated number of observations from the immediate past. Overall, since the combination methods consume extra months after the univariate predictions, I adopt the logic to include as many periods as possible around the same sample period, instead of trim the sample to exclude historical observations.

2.5 Statistical Tests and Economic Gains

I include the OOS tests as the main tests of my study. In the OOS test setup, the OOS predictions are based on IS models that have never seen the OOS realized values. Then, the predicted value is compared against realized value for statistical tests. OOS test setup is the standard setup for return predictability literature. Such setup provides the most rigorous and relevant evidence about return predictability (Dong et al. 2020, Martin and Nagel 2021, Goyal and Welch 2008). I apply the tests to all the prediction setups in a rolling manner such that I get the time variation of the OOS performance.

The main statistical metric in OOS test is the OOS R-square (Lettau and Ludvigson 2001, Campbell and Thompson 2008, Goyal and Welch 2008), defined as:

$$R^2 = 1 - \frac{\sum_{t=T_1}^{T}(r_t - \hat{r}_{t|t-1})^2}{\sum_{t=T_1}^{T}(r_t - \bar{r}_{t|t-1})^2}, \tag{5}$$

where T_1 is the starting period of prediction, $\hat{r}_{t|t-1}$ is the alternative prediction made with my setups, $\bar{r}_{t|t-1}$ is the null prediction of expanding window moving average, and r_t is the realized ground truth equity premium.

The standard statistical test for OOS predictability is the Clark and West test (See Clark and McCracken 2001, Clark and West 2007, Goyal and Welch 2008, etc.). I report the statistical significance of OOS tests based on the Clark and West test.

Beyond the statistical test, Campbell and Thompson (2008) proposed the use of mean-variance investor 's certainty equivalent return (CER) as a measure of OOS predictability for economic interpretation (Goyal and Welch 2008, Rapach et al. 2011 among other early adopters). The idea is to capture the return-variation trade-off. Following the literature, I define CER as:

$$CER = \mathbb{E}[R_p] - (\frac{\gamma}{2}) \cdot Var(R_p), \tag{6}$$

where R_p is the portfolio return and I specify the risk aversion coefficient $\gamma = 3$.

The CER of a prediction has to be interpreted against the CER generated by the null model, i.e., the expanding window mean. The difference between a model 's CER and the null model 's CER is CER gain. I report CER gains for all of my prediction setups.

3 Out-of-Sample Results

I report the OOS test results for the UK. In order to cross-refer the performance for the UK predictability and the transfer learning results in Section 4, I also include the OOS test results for the US.

Because of the differences in the data availability, I split the sample into 2 parts for each market. The first UK sample covers 171005:201612 with the predictions starting from 171505, while the second UK sample covers 185402:201612 with the predictions starting from 185902. the The first US sample covers 185702:202012 with the predictions starting from 186202, while the second US sample covers 192602:202012 with predictions starting from 193102.

3.1 Predictive Regressions

Following the literature, I provide an examination of the univariate predictive regressions. These regressions take the the following form,

$$r_{t+1} = \beta_0 + \beta_1 x + \varepsilon_{t+1}, \tag{7}$$

where r_{t+1} is the equity risk premium at time $t+1$ and x_t is the prevailing value of a predictor. The regressions are performed over all availability of the associated predictor.

The predictive regressions can often directly us to predictors that deliver consistent OOS performances. However, the predictive regressions are considered as a weak test for predictability analysis, since all IS tests have huge exposure to model overfitting. In real time, predictors selected from IS analysis are likely not to deliver any performance (Goyal and Welch 2008, Martin and Nagel 2021, Rapach and Zhou 2020).

[INSERT TABLE 2 HERE]

Table 2 presents the regressions. Because of the limited availability, the regressions are fit to two samples for each of the markets. Panel A shows the results for the UK and Panal B shows the results for the US. In general, many regressions signify the importance of the predictors in the IS analysis. For example, dividend yield is very significant for the entire three-hundred-year sample in the UK and the significance lasts in the shorter sample from 1854, consistent with the annual results of IS regressions from Golez and Koudijs (2018).

However, in the US market, dividend yield is not as significant in the IS analysis for the period from 1926. Neither is dividend price. On the other hand, the technical indicators in the US are quite significant. For example, the moving average indicator $ma_{1,9}$ is very significant.

It is also worth to note that the past equity premiums seem predicting the future equity premiums in both markets with the strongest statistical significance. The past equity premiums seem understudied in the recent return predictability literature. Yet, it is an important and fundamental variable for the return predictability. In general, we should not expect that the lagged equity premiums can successfully predict the future equity premium in the OOS tests.

The strongest macroeconomic predictors are return on long-term bond and term spread in the UK and treasury bill in the US, emphasizing the importance of investigating interest rate related predictors over the long run. In the end, it is also interesting to note that the macroeconomic predictors in the US market seem extremely weak in the IS regressions. However, in the next subsection, we can see that these macroeconomic predictors actually can deliver very significant OOS performance.

3.2 A Three-Hundred-Year Out-of-Sample Test

In this subsection, I present the main results of the three-hundred-year OOS tests for the UK market. The predictions start from May 1715 and end in December 2016. I focus on the OOS R^2 as the main metric and provide the evaluation across different time windows.

Table 3 is organized by sample coverage. As mentioned, instead of trimming the sample coverage such that all methods start from the same date, I provide the results with the longest possible coverage such that all the real variations of predictability are considered as long as the data permit. Note that the slight difference in coverage does not lead to meaningful change in the testing power, considering the sample size. This is because of the nature of Clark-West Test (Clark and West 2007, Clark and McCracken 2001) and a normal test can have enough testing power to reject alternative hypothesis with my sample sizes.

Admitted, the minor difference in the coverage may lead to slight advantages to different predictions because of coverage. However, trimming the sample to align the starting dates of predictions will absolutely lead to the loss to coverage in the earlier periods, which can become a barrier of developing a better long-run understanding of the predictability.

[INSERT TABLE 3 HERE]

Panel A shows the longest OOS tests of monthly return predictability in the literature, the three-hundred-year OOS predictability tests for the UK monthly data. Because of the limited availability, Panel A focuses on the technical indicators (Neely et al. 2014) along with, arguably, the most important macroeconomic variables, dividend yield and dividend price (Bansal and Yaron 2004, Campbell and Shiller 1988b). The panel presents 3 test results for each of the 62 prediction setups.

In general, most of the models *failed* to demonstrate significant OOS performance over the three hundred years, questioning the effectiveness of technical indicators in the long run, contrary to the findings from Rapach et al. 2011. Most of these prediction setups, either rolling updated or expanding updated, have negative OOS R^2, indicating complete underperformance to the null prediction from the expanding moving average of the equity premium. Interestingly, the top performer over the three hundred years is the lagged equity premium, delivering a three-hundred-year annualized OOS R^2 of 4%. However, the performance from the past equity premium vanished in the tests of recent samples. Overall, the predictability is disappointing and only 4 setups out of 62 setups included in the 300-year tests show OOS R^2 greater than 1%. The best performer for the last-50-year sample in the UK is the dividend yield, delivering an OOS R^2 of 2%, followed by dividend price, delivering an OOS R^2 of 0.9%.

It is necessary to emphasize the volatility of the predictability, which can bring in short-term performance that are significantly high comparing the predictors'long-run performance and potentially can throw off the results with just several years in the sample. If we focus on the last-5-year sample, the setups updated with a 20-year window demonstrate huge advantages. The top performer is dividend price, updated with a 20-year window, with a huge 21.6% annualized R^2 followed by dividend yield, also updated with a 20-year window, delivering a huge 18.8% annualized R^2. The technical indicators such as $MA_{1,12}$ also demonstrate powerful short-term predictability with the 20-year updating window. In fact, this short-term performance signals huge volatility of the predictability, if we compare the short-term tests with the long-run tests. In Section 5, I report the standard deviations of short-term predictability measured with 5-year rolling window OOS R^2s and it will be clearer that all OOS tests need to be treated with extra caution given the huge contrast of the overall predictability level and the fluctuations.

I show the OOS test results for the UK during the period 185902:201612 in Panel B. Panel B mainly focuses on macroeconomic predictors, since all macroeconomic predictors considered in this paper became available around 5 years ago before the first prediction in February 1859. Similar to the technical indicator setups and the dividend ratio setups in the super long run, most macroeconomic setups *do not* show significant performance in the OOS performance. However, more predictors do show positive OOS R^2s. The top performer for the one-hundred-fifty-seven-year sample is the return on the long-term bond, followed by the forecast combinations, term spread and dividend yield. Overall, it is noticeable that the macroeconomic setups are surprising more consistent through different samples. Most of the top performers stay outperforming the null model for the other two testing samples. The return on long-term bond delivers a surprisingly 24.5% OOS R^2 in the last 5 years of my sample coverage. The persistent performance of forecast combination models are consistent with the documentation in the literature (Rapach and Zhou 2021, Rapach et al. 2011). However, again, the huge difference between the short sample performance and the long sample performance urges further investigation on the fluctuation of predictability.

Panel C and D show the counterparts of Panel A and B for the US market. Because of the difference in data availability, I include the tests for the technical indicators starting from February 1863 and I include the tests for the macroeconomic setups starting from February 1931. Surprising, despite the same setup, the technical indicators in Panel C are a lot more successful in the US market comparing to the UK market of their corresponding sample periods. The forecast combination, C-Mean (Rapach et al. 2011), demonstrate a 4% OOS R^2 followed by the past equity premium with a 3.6% OOS R^2. Even predictors that deliver the worst performance in the UK show significant performance over the long run in the US market, signifying the subtle difference between the two markets in the long run. For example, standard deviation, which delivers a such poor performance of -8.6% OOS R^2 in the last 50 years in the UK sample and -7.1% OOS R^2 in the entire UK sample, shows 1% OOS R^2 and 1.6% OOS R^2 for the last 50 years in the US sample and in the entire US sample respectively. Interestingly, many more predictors turned significant performers in the last 50 years in the US market, indicating that the US market seem becoming more predictable in this recent sample. However, we should not over-interpret this result. As mentioned, there exists significant short-term variation of the predictability, any sample coverage change can lead to different test results.

Panel D shows the OOS tests over the shorter sample in the US. Almost all successful predictions are made with forecast combinations. However, inflation seems also a very important predictor, presenting consistent predictability over all three samples, while inflation in the UK is a weak predictor.

In general, these tests demonstrate the existence of the OOS predictability in the corresponding samples. In fact, Campbell and Thompson (2008) argue that even a very small R^2 can signal meaningful predictability. However, the predictability is so limited to certain variables in the macroeconomic setups. Most of the predictor $failed$ to deliver any OOS performance in the long run, indicating that the market is fairly efficient. The change of significance in the recent 100 years show that the efficiency seems improving.

Overall, we also have to be cautious when interpreting the predictability from these panels. It is possible that the sample selection may lead to different testing results, since there may exist huge short-term variations of the predictability. For example, there are predictors realizing huge OOS R^2 in the last 5 years in the sample. Yet, they show OOS R^2s only slightly above 0 in the entire sample. I discuss more details of the predictability fluctuations in Section 5.

3.3 Economic Gains in Three Hundred Years

Campbell and Thompson (2008) argue that increasing return levels of a portfolio can also increase the risk (See also Kandel and Stambaugh 1996, Barberis 2000). Thus, observing higher returns in a portfolio does not indicates a higher utility gain. They proposed the use of certainty equivalent return (CER) as the metric to compare the utilities and they demonstrate the CER gains calculated as the difference between the CER of an alternative prediction and the CER of the null prediction. I follow their method and report the economic gains measured with CER. In the CER calculation, I specify $\gamma = 3$.

I report the CER gains in Table 4. Table 4 is organized in the same logic as the organization of Table 3. Panel A and B show the results for the predictions in the UK market and Panel C and D show the results for the predictions in the US market. In addition to the CER gains, I also show relative turnover, which is a ratio of alternative prediction portfolio turnover over the null prediction portfolio turnover.

[INSERT TABLE 4 HERE]

The results from Campbell and Thompson (2008) show broad correlation between the OOS R^2s and the CER gains. The broad correlation also shows up in my results. Most of the top economic gainers also deliver the best R^2. Panel A and B seem to note that the combinations have an edge over the other setups. Over the long run, the gains for the top forecast combinations are all above 1% annualized. Many setups seem to require only 3 times of the turnover comparing to the turnover of the portfolio from the long-run expanding average. Similar to the statistical performance, the economic gains are only delivered from a limited group of prediction setups, mainly the forecast combinations, questioning the possibility of realizing anything from other prediction setups.

The US market, on the other hand, shows completely different results. In Panel C and D, most of the prediction setups, with either technical indicators or macroeconomic predictors, show positive gains, regardless of their statistical performance. The past equity premium realized a gain close to 3% annualized in the long sample. The forecast combination based on ENet updated with 20-year rolling window realized a gain close to 3% as well. These results show that the investors can benefit from a wide range of possible market predictions in the past one hundred sixty years in the US market. In other words, it seems that the US market is a luckier market, in term of realizing prediction-based economic gains, comparing to the UK market.

In general, the economic gains many prediction setups also decrease by large through time. Figure 4, 5, 6 and 7 demonstrate the top economic CER gains over time. Each of these figures show two calculations, one for the expanding window CER gain, where I calculate CER gain at every period using all past performance, and another for the 50-year expanding window CER gain, where I calculate the CER gain at every period but using past 50-year performance. As shown, 3 of the top performers from the two markets show decreasing CER gains. The CER gains from technical indicator combined with C-ENet also decreases substantially towards the end of the sample period.

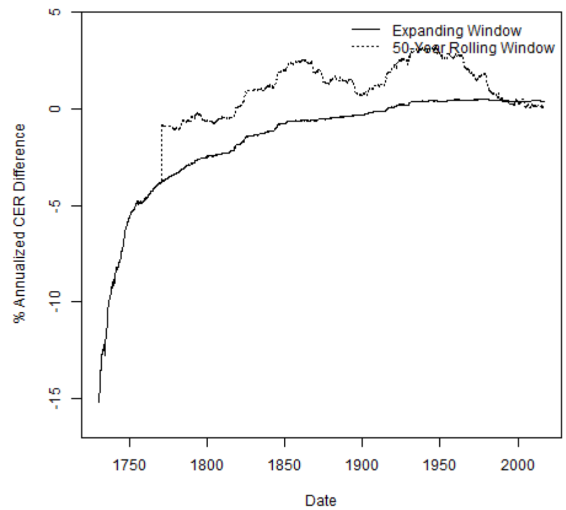

Figure 4: UK Expanding Window Update Technical Indicator C-ENet Combination CER Gains

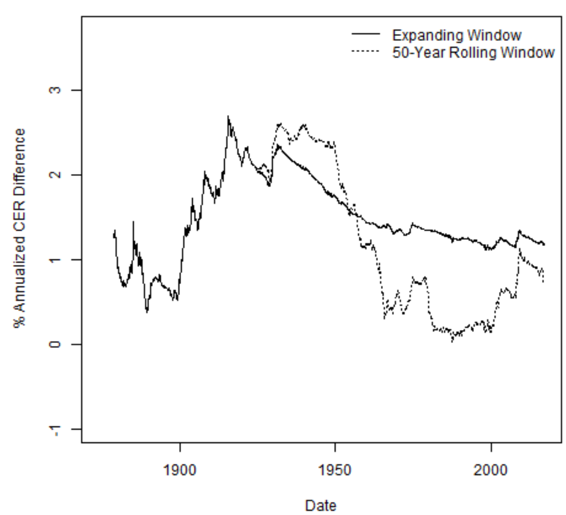

Figure 5: UK 20-Year Rolling Window Update Macroeconomic Predictor DMSPE Combination CER Gains

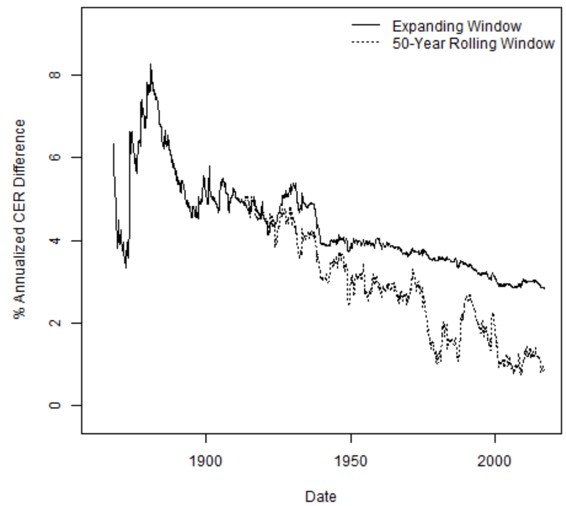

Figure 6: US Expanding Window Update Lag 1 Equity Premium CER Gains

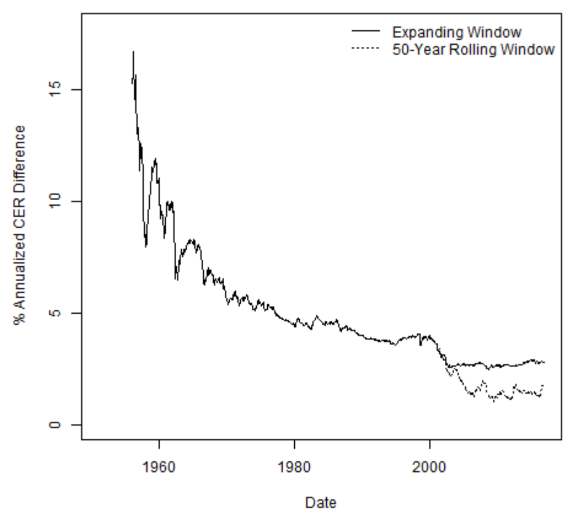

Figure 7: US 5-Year Rolling Window Update Macroeconomic Predictor C-ENet Combination CER Gains

4 Transferable Predictability: from the UK to the US

Rapach et al. (2013) are the pioneers to investigate the predictability based on the information from one market to another market. Jiang et al. (2020) are the pioneers in official tests of transfer learning predictability at the stock level using image model trained with the US data. Taking the advantage of the simultaneous observation of the two most import market in the past couple centuries, I study the transferability of the predictability in the long run based on the common predictors in the return predictability literature.

In short, I fit the models with the UK data and apply the fitted models to the US market. I roll forward the prediction process for each period in my sample with observations in both the UK and the US markets. Then, I construct OOS testing statistics along with the CER gains.

4.1 Transfer Learning Out-of-Sample Tests

In theory, if the investors are all mean-variance optimizers, they will allocate their funds following the same logic, leading to the universal market wisdom that can be applied to the same market of mean-variance optimizers. This means that we should expect the market wisdom is transferable and universal. In other words, if we fit models with the UK data and apply the models to the US market, we should realize some performance similar to the performance in the UK.

My tests confirm this hypothesis. Table 5 and Table 6 show the counterparts of Table 3 and 4 for the transfer learning setups where I fit exactly the same common prediction setups from Table 3 and 4 with the UK data and apply the predictions in the US market. Table 5 reports the OOS tests and Table 6 reports the economic gains. The tables are organized in the similar ways as in their counterparts from Table 3 and Table 4.

[INSERT TABLE 5 HERE]

The models based on the UK data achieve huge success, much better than their performance in the UK market itself. About a half of the models realized significant OOS R^2. The past equity premium in the 20-year updating window setup show an OOS R^2 of 7.3%. Macroeconomic forecast combination also shows 3% OOS R^2. Similar to Table 4, the performance from technical indicators vanished in the recent sample periods. However, the predictability in the shorter sample demonstrates such consistency that they are often effective across the samples. In general, the OOS results are better than the results from the predictions based on modeling with US data.

Interestingly, despite being proxied with substantial differences, macroeconomic predictors such as treasury bill, return on long turn bond, term spread, inflation and long term yield all deliver significant OOS R^2 indicating the success of my proxy strategies. However, dividend yield and dividend price are found without meaningful predictability, although they perform well in the last 50 years of the UK sample. Again, we should not generalize the results. The top performers in transfer learning setups are also included in Figure 2 of Section 1. They also show huge short-term predictability fluctuations.

4.2 Transfer Learning Economic Gains

[INSERT TABLE 6 HERE]

Table 5 shows the economic gains of the transfer learning setups. Surprisingly, the transfer learning setups can realize higher economic gains comparing to the economic gains from the US models. For example, the past equity premium delivers a CER gain at 3.5% level, while the macroeconomic predictor C-Mean delivers a CER gain of 3.38%, even higher than what Dong et al. (2020) present in their sample from 1985.

Briefly, Table 5 and Table 6 jointly demonstrate the possibility of investors learning from one market and applying the common wisdom to another market. Both the predictability and the economic gains are stronger at their absolute level relative to their counterparts of US results in Table 3 and Table 4.

Figure 8 and Figure 9 demonstrate the two top economic gainers. In general, the CER gains are also decreasing for transfer learning, especially for the recent periods.

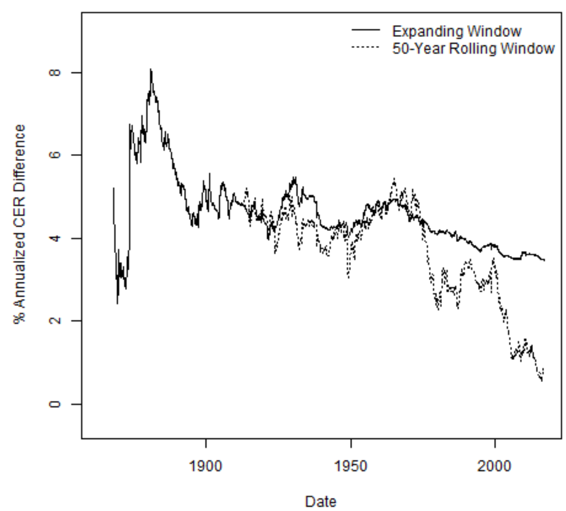

Figure 8: US 20-year Rolling Window Update Lag 1 Equity Premium CER Gains

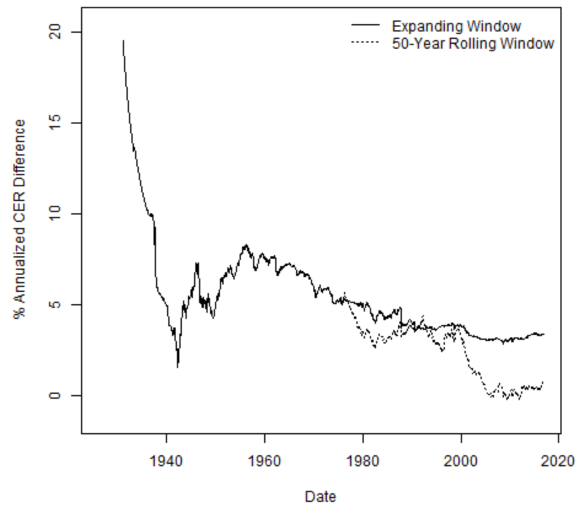

Figure 9: US 5-Year Rolling Window Update Macroeconomic Predictor Mean Combination CER Gains

5 The Stability of Out-of-Sample Predictability

Table 3 and Table 5 present the existence of OOS predictability with different prediction setups. The inconsistency between the sample coverage signals short-term fluctuations that may dominate the OOS tests and cause disagreement in the literature. Therefore, we have to be cautious when interpreting the OOS test results. To better understand the possible influence of such fluctuations in predictability, I calculate the 5-year rolling window monthly OOS R^2s for each prediction setup. I report the standard deviations of the OOS R^2s, as a measure of stability of predictability, in Table 7. All results in Table 7 are annualized standard deviations of the short-term monthly OOS R^2s. I report the results for technical indicators and macroeconomic predictors in Panel A and Panel B, respectively.

[INSERT TABLE 7 HERE]

Both Panel A and Panel B show that the all predictors are associated with huge volatility that are of multiple folds of their corresponding annualized OOS R^2s based on the monthly predictions. For example, in the UK market, lag1 equity premium has a standard deviation in predictability of 0.325 in the expanding window setup, while its OOS R^2 is only 4%. The standard deviation of its predictability over the super long run is 8 times of the realized predictability. In other words, the predictability of lag1 equity premium can suddenly show up and then decrease tremendously in a very short period. Such a large fluctuation can change the results of statistical tests on the R^2 quickly, leading to different conclusions between sample coverage, since a one-standard deviation event is not a rare event and can easily happen with a probability of 32% under Gaussian distribution assumption. This signifies the importance to investigate the long-run predictability and warns us *not to* overgeneralize the information provided by OOS tests in the literature (Goyal et al. 2021, Goyal and Welch 2008).

Figure 1 and Figure 2 in Section 1 also present a comparison between the long-run predictability and the short-term fluctuation of the predictability. In particular, Figure 2 shows that the top performers in terms of OOS R^2 can demonstrate huge short-term fluctuations in their performance and the overall performance many just come from the short-term peaks of the predictability.

Overall, there is a general correlation between the consistency of predictability and its fluctuation. Successful predictors in all samples of Table 3,4,5 and 6, such as the forecast combinations, have relatively lower volatility in short-term predictability comparing to others'. Statistically, if a predictor has a low predictability volatility, we can be more confident with its long-run test results. However, we have to be very cautious when interpreting results of predictors with very high predictability fluctuation, such as the results of lag1 equity premium, long term yield and default yield spread.

6 GDP and Extreme Return Months

The asset pricing literature emphasizes the overlap between the realization of predictability and economic downturns. Cespa and Vives (2011) theoretically show that the disagreement among the investors can lead to significant predictability during the times with economic uncertainty. Empirically, there seems an overlap between the OOS R^2 and the business cycle (Rapach et al. 2011, Neely et al. 2014, Fama and French 1989). However, it is not clear that when the predictability is realized during the GDP downturns. Empirically, when the economic situation is uncertain, the market becomes volatile, leading to extreme returns. Is it possible that the OOS R^2s are earned during the interaction period between GDP downturns and the extreme equity premium? To answer this question, focusing on the long history of the UK data and the successful predictors, I calculate the OOS R^2 conditionally on the GDP situations and extreme returns and average the OOS R^2s across the predictors from Table 3 with positive OOS R^2s in the entire UK sample. I report the results in Table 8. To accommodate the possibility that the predictability is mainly due to rare economic events (Barro 2009), I also consider the extreme GDP decreases.

[INSERT TABLE 8 HERE]

Many papers have documented the concentration of the predictability in the US market during recession (Rapach et al. 2011). Panel A confirms this observation with the new UK evidence but is a more limited period. The predictability seems realized when GDP is extremely negative or when GDP is turning either positive or negative. In other words, it may not be the recession but the time points, where the economic state changes, that contribute to the predictability.

Panel B shows that the predictability is mainly concentrated in the positive extreme return months. This observation is interesting. Many studies argue that the arbitrage asymmetry leads to overreaction and predictability (Dong et al. 2020, Stambaugh et al. 2015). The predictability concentration in positive extreme equity premium months supports this argument that the predictability is realized when the price bounce back from the low point induced by the liquidity and when the price is too high for the arbitrageurs to do anything to bring it down.

I investigate the interaction between the economic situation and the extreme returns. Panel C shows the concentration of the predictability over certain interaction periods of the economic situation and the extreme returns. Specifically, I consider different combination of the GDP turning points and the extreme equity premiums. In summary, Panel C shows that the predictability concentrates in the periods when GDP is turning negative and there is an extreme equity premium.

Specifically, the predictability coming from the general interaction are specifically concentrates in the periods when GDP turns positive and there is an extreme positive equity premium and when the GDP turns negative and there is an extreme negative premium. In other words, the predictability concentrates in limited time periods when the economy enters in bad state and when the economy comes out from the bad state. The effects from the extreme returns are also conditional and asymmetry. This finding of asymmetric effects coming out from the interaction between economic state and equity premium supplements the findings in the literature that documents the overlap between recession and predictability.

7 Rare Events and Seasonality

With the UK history going back to the early 19th century, when historical rare events beyond historical downturns happen more frequently, I investigate further the effects from the non-economic rare events, including famine, epidemic, pandemic and major wars. I study the concentration of the predictability across these rare event years. Note that these non-economic rare events are not directly led by the economic situation but can lead to economic downturns. However, after marking the event years with dummy variables, I calculate the Cramer's V between the GDP decrease and the rare events and the categorical variable correlation is just 0.07, indicating weak correlation.

Specifically, I consider the following events in their corresponding years,

1729: Influenza Pandemic

1740: The Great Frost and Irish Famine

1756-1763: Seven Years War

1775-1776: England Influenza Outbreak

1775-1783: American Revolutionary War

1798-1815: Fourth Anglo-Mysore War, Second Mahratta War, Peninsular War, and Napoleonic War

1816: Year without Summer

1831-1833: The Second Cholera Pandemic

1836-1840: Influenza Pandemic and Smallpox Epidemic

1845: The Great Irish Famine

1847-1848: Influenza Pandemic

1848: The Third Cholera Pandemic

1865: The Fourth Cholera Pandemic

1870-1875: Europe Smallpox Epidemic

1889-1890: Flu Pandemic

1914-1918:World War I

1918: Spanish Flu Pandemic

1939-1945: World War II

1957: Asian Flu Pandemic

1968: Hong Kong Flu Pandemic.

The above list only includes natural disasters of thousands or more deaths and wars of casualties above 25,000. To supplement the events in case of not included rare events, I calculate the population change and include it as a condition for OOS R^2s. Table 9 shows the OOS R^2 calculated conditional on the events. As in Table 8, I focus on the average of OOS R^2s from the predictors with positive R^2 in Table 3. In short, the OOS predictability concentrates in famine years and years with contagious diseases. The concentration during the war times are minor. Population decrease overall does not contribute to predictability.

[INSERT TABLE 9 HERE]

In addition, taking the two markets together, I calculate the OOS R^2s conditional on calendar months. Figure 10 and 11 present the seasonality. In general, I show that the predictors gain predictability mainly in colder months during fall and spring in both the UK and the US markets. The predictability is at its lowest during summer.

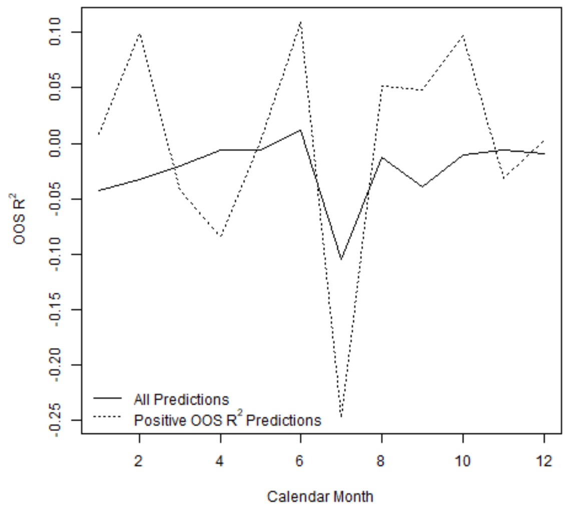

Figure 10: UK OOS R^2 by Calendar Months

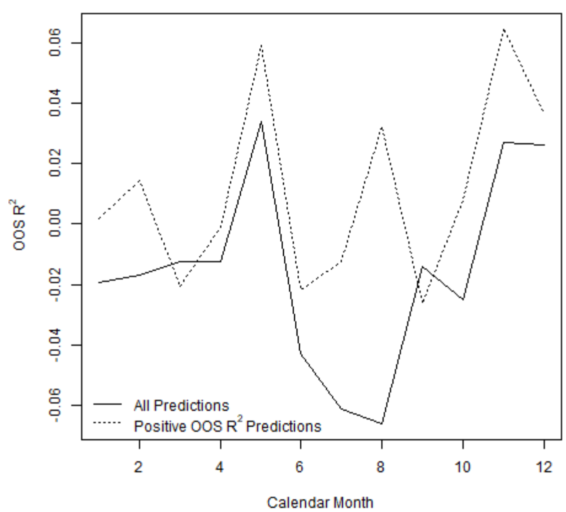

Figure 11: US OOS R^2 by Calendar Months

8 Conclusion

Although the return predictability literature is very active with different evidences covering samples mainly of the past 70 years, only limited attention has been paid towards the predictability over the real long run and thus there lacks evidence over the big picture. This paper is the first to consider a real long-run sample, a UK data set of 300-hundred years, to test the monthly return predictability with a variety of common prediction setups. Despite the existence of predictability in the long history, my setup confirms the general trend of declination in predictability in the past 100-200 years and demonstrates the strong predictability fluctuations. The demonstration of predictability fluctuations rationalize the findings from Goyal et al. (2021), i.e., small changes in sample coverage can lead to different OOS test results. This urges extra caution when interpreting OOS test results.

Over the long run, predictions may not lead to economic gains in the UK, but most of the prediction setups can lead to positive CER gains in the US, implying the subtle difference between the UK and the US. This paper also confirms that adopting rolling updating window does not lead to dominating performance. Generally, expanding window and the relatively longer rolling window show better performance as groups comparing to the short 5-year rolling window.

In a full scale transfer learning test, with the US data as the target, I confirm that the predictability of common setups is transferable. The models fitted with the UK data lead to sizable economic gains that are larger than the economic gains brought up by the models fitted with the US data, possibly because of the longer history included in the training process with the UK data. However, CER gains also decrease in general in the UK tests, the US tests and the transfer learning tests, leading to a question on the persistence of the prediction-led economic gains.

On the side, with the long and well-documented UK history, I investigate the sources of the predictability conditional on the critical moments. I show that the predictability mainly exists in the deeply negative GDP periods, not just the negative GDP or recession periods. In addition, I demonstrate the interaction between the GDP dynamics and the extreme return months. The interaction plays an important role in realizing OOS predictability. Specifically, predictability is earned mostly from the periods when the GDP is turning negative and the equity premium is extremely negative and when the GDP is turning positive and the equity premium is extremely positive.

The predictability also concentrates in the famine years, the epidemic years and the pandemic years. However, the predictability does not concentrate in the years of wars, despite the huge impact of WWI and WWII, nor the years with decreasing population. On average, predictability concentrates in the colder months and the summer is the worst to realize any meaningful predictability.

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Table 1: Summary Statistics

Table 1 shows the summary statistics for the four main samples covering. Panel A and B shows the statistics for 171005:201612 and 185401-201612 in the UK, while Panel C and D shows the statistics for 185702:202012 and 192602:202012 in the US. The first column in each panel indicates the predictor.

Panel A: UK Summary Statistics 171005-201612

Variable	Mean	Sd	Q1	Median	Q3
equity premium	0.002	0.034	-0.011	0.002	0.015
dy	-3.217	0.29	-3.459	-3.193	-2.996
dp	-3.221	0.29	-3.463	-3.193	-3.006
ma_1_9	0.503	0.5	0	1	1
ma_2_9	0.567	0.496	0	1	1
ma_3_9	0.501	0.5	0	1	1
ma_1_12	0.503	0.5	0	1	1
ma_2_12	0.578	0.494	0	1	1
ma_3_12	0.512	0.5	0	1	1
lag1	0.002	0.034	-0.011	0.002	0.015
lag2	0.002	0.034	-0.011	0.002	0.015
lag3	0.002	0.034	-0.011	0.002	0.015
mean9	0.002	0.013	-0.004	0.002	0.008
mean12	0.002	0.011	-0.003	0.002	0.007
mom9	0.726	0.446	0	1	1
mom12	0.738	0.44	0	1	1
sd	0.035	0.009	0.029	0.033	0.036
skew	-0.717	0.323	-0.873	-0.825	-0.765
kurt	49.032	15.705	38.671	52.893	59.675

Panel B: UK Summary Statistics 185402-201612

Variable	Mean	Sd	Q1	Median	Q3
equity premium	0.003	0.037	-0.009	0.004	0.019
dy	-3.07	0.228	-3.18	-3.058	-2.919
dp	-3.077	0.232	-3.194	-3.064	-2.931
ma_1_9	0.516	0.5	0	1	1
ma_2_9	0.632	0.482	0	1	1
ma_3_9	0.508	0.5	0	1	1
ma_1_12	0.509	0.5	0	1	1
ma_2_12	0.645	0.479	0	1	1
ma_3_12	0.525	0.499	0	1	1
lag1	0.003	0.037	-0.009	0.004	0.019
lag2	0.003	0.037	-0.009	0.004	0.019
lag3	0.003	0.037	-0.009	0.004	0.019
mean9	0.003	0.014	-0.002	0.003	0.01
mean12	0.003	0.012	-0.002	0.003	0.009
mom9	0.775	0.417	1	1	1
mom12	0.786	0.41	1	1	1
sd	0.023	0.009	0.015	0.022	0.034
skew	-0.499	0.41	-0.727	-0.647	-0.174
kurt	8.852	6.112	3.741	7.401	14.851
tbl	0.043	0.033	0.019	0.037	0.056
lty	0.049	0.029	0.031	0.037	0.052
ltr	0.001	0.03	-0.01	0	0.01
tms	0.006	0.018	-0.005	0.007	0.019
dfy	0.008	0.005	0.005	0.008	0.01
dfr	0.004	0.086	-0.034	0.005	0.042
infl	0.031	0.093	-0.008	0.021	0.057

Panel C: US Summary Statistics 185702:202012

Variable	Mean	Sd	Q1	Median	Q3
equity premium	0.003	0.047	-0.02	0.005	0.029
ma_1_9	0.513	0.5	0	1	1
ma_2_9	0.54	0.499	0	1	1
ma_3_9	0.484	0.5	0	0	1
ma_1_12	0.512	0.5	0	1	1
ma_2_12	0.544	0.498	0	1	1
ma_3_12	0.488	0.5	0	0	1
lag1	0.003	0.047	-0.02	0.005	0.029
lag2	0.003	0.047	-0.02	0.005	0.029
lag3	0.003	0.047	-0.02	0.005	0.029
mean9	0.003	0.018	-0.007	0.004	0.014
mean12	0.003	0.016	-0.007	0.004	0.013
mom9	0.677	0.468	0	1	1
mom12	0.679	0.467	0	1	1
sd	0.044	0.007	0.035	0.047	0.048
skew	-0.365	0.182	-0.418	-0.35	-0.248
kurt	6.547	3.769	2.646	8.628	10.225

Panel D: US Summary Statistics 182602:202012

Variable	Mean	Sd	Q1	Median	Q3
equity premium	0.005	0.054	-0.02	0.01	0.035
dy	-2.322	0.628	-2.95	-2.307	-1.719
dp	-2.325	0.628	-2.951	-2.309	-1.723
ma_1_9	0.516	0.5	0	1	1
ma_2_9	0.589	0.492	0	1	1
ma_3_9	0.468	0.499	0	0	1
ma_1_12	0.522	0.5	0	1	1
ma_2_12	0.604	0.489	0	1	1
ma_3_12	0.482	0.5	0	0	1
lag1	0.005	0.054	-0.02	0.01	0.035
lag2	0.005	0.054	-0.02	0.01	0.035
lag3	0.005	0.054	-0.02	0.01	0.035
mean9	0.005	0.019	-0.003	0.008	0.017
mean12	0.005	0.017	-0.003	0.007	0.015
mom9	0.739	0.439	0	1	1
mom12	0.749	0.434	0	1	1
sd	0.065	0.015	0.056	0.06	0.072
skew	-0.338	0.245	-0.396	-0.337	-0.279
kurt	6.413	2.125	4.985	7.7	7.843
tbl	0.033	0.031	0.004	0.029	0.051
lty	0.05	0.028	0.028	0.041	0.068
ltr	0.005	0.025	-0.007	0.003	0.016
tms	0.017	0.013	0.008	0.017	0.026
dfy	0.018	0.009	0.011	0.017	0.023
dfr	0	0.014	-0.005	0	0.006
infl	0.03	0.04	0.013	0.026	0.043

Table 2: Predictive Regressions

Table 2 reports the results of the in-sample (IS) univariate predictive regressions for the predictors'longest availability of the two samples. The two samples for each market are constructed to accommodate the different variable availability. In general, longer samples focus on technical indicators and the shorter samples focus on macroeconomic predictors. The only exception is that the dividend yield and the dividend prices are also included in the longer sample of the UK market. Panel A and B shows the results for the UK and the US markets respectively. Panel A includes the two samples of the UK market and Panel B includes two samples of the US market.

Panel A: UK Predictive Regressions

Predictor	Coeff	T Stat	R2	Coeff.1	T Stat.1	R2.1
dy	0.007	3.634	0.004	0.01	2.838	0.004
dp	0.005	2.463	0.002	0.007	2.056	0.002
ma_1_9	0.003	3.033	0.002	0.002	1.436	0.001
ma_2_9	-0.005	-4.746	0.006	-0.007	-3.875	0.008
ma_3_9	0.003	2.444	0.002	0.001	0.828	0
ma_1_12	0.003	3.022	0.002	0.002	1.153	0.001
ma_2_12	-0.005	-4.257	0.005	-0.005	-2.741	0.004
ma_3_12	0.002	2.012	0.001	0	0.034	0
lag1	0.161	9.884	0.026	0.105	4.663	0.011
lag2	0.007	0.408	0	-0.058	-2.546	0.003
lag3	0.042	2.539	0.002	0.054	2.374	0.003
mean9	0.123	2.839	0.002	0.167	2.698	0.004
mean12	0.156	3.115	0.003	0.213	3.049	0.005
mom9	0.005	3.717	0.004	0.004	2.056	0.002
mom12	0.004	2.952	0.002	0.004	1.843	0.002
sd	-0.213	-3.273	0.003	0.143	1.488	0.001
skew	0.003	1.512	0.001	0	0.176	0
kurt	0	-0.941	0	0	2.805	0.004
tbl				-0.035	-1.362	0.001
lty				0.009	0.289	0
ltr				0.106	3.761	0.007
tms				0.138	2.959	0.004
dfy				0.216	1.363	0.001
dfr				-0.009	-0.898	0
infl				-0.002	-0.211	0

Panel B: US Predictive Regressions

Predictor	Coeff	T Stat	R2	Coeff.1	T Stat.1	R2.1
ma_1_9	0.007	3.33	0.006	0.004	1.151	0.001
ma_2_9	-0.008	-3.835	0.007	-0.006	-1.813	0.003
ma_3_9	0.002	0.946	0	-0.002	-0.469	0
ma_1_12	0.008	3.734	0.007	0.005	1.478	0.002
ma_2_12	-0.009	-4.227	0.009	-0.005	-1.577	0.002
ma_3_12	0.001	0.643	0	-0.003	-0.931	0.001
lag1	0.128	5.706	0.016	0.082	2.767	0.007
lag2	-0.004	-0.193	0	-0.018	-0.618	0
lag3	-0.059	-2.628	0.004	-0.092	-3.098	0.008
mean9	0.244	4.089	0.008	0.166	1.961	0.003
mean12	0.263	3.976	0.008	0.175	1.84	0.003
mom9	0.009	4.097	0.009	0.008	2.172	0.004
mom12	0.009	4.161	0.009	0.006	1.747	0.003
sd	0.53	3.415	0.006	0.081	0.741	0
skew	0.013	2.287	0.003	0.02	3.129	0.009
kurt	0.001	3.093	0.005	0	-0.565	0
dy				0.001	0.204	0
dp				0	0.104	0
tbl				-0.092	-1.765	0.003
lty				-0.08	-1.395	0.002
ltr				0.097	1.479	0.002
tms				0.142	1.149	0.001
dfy				0.086	0.503	0
dfr				0.165	1.445	0.002
infl				-0.042	-1.04	0.001

Table 3: Out-of-Sample Tests: in 300 Years

Table 3 reports the main results from out-of-sample (OOS) tests. To accommodate the different variable availability, Panel A through Panel D show results for the UK market and the US market in different periods. Panel A reports results mainly focusing on dividend yield, dividend price and technical indicators for the longest sample in the UK market. Panel B reports the results of macroeconomic variables in the UK. Panel C and D reports the counter parts of Panel A and B for the US market. The column "update" indicates the model updating scheme, including expanding window update using all past observations, 60-month rolling window using past 60 months and 240-month rolling window update using past 240 months. The column "last 50 year" shows the OOS R^2 for the last 50 years in the sample and the column "last 5 year" shows the OOS R^2 for the last 5 years in the sample. The "all year" column shows the OOS R^2 for the entire sample. The p values to the right of the testing windows are from the Clark and West test. The OOS R^2s are annualized.

Panel A: UK OOS Tests 171505:201612

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
lag1	1715-05	2016-12	Expanding	-0.358	0.077	0.003	0.169	0.04	0.015
return_c_enet	1720-05	2016-12	Expanding	-0.012	0.752	0.01	0.256	0.017	0.012
ma_2_9	1715-05	2016-12	Expanding	0.02	0.552	0.014	0.108	0.014	0.013
return_cmean	1715-05	2016-12	Expanding	-0.019	0.58	0.009	0.272	0.013	0.475
ma_2_12	1715-05	2016-12	Expanding	-0.028	0.986	0.005	0.322	0.01	0.029
mom9	1715-05	2016-12	Expanding	-0.03	0.778	0.005	0.469	0.007	0.027
return_cmean	1730-05	2016-12	Rolling 240	0.023	0.515	-0.029	0.755	0.003	0.116
mom12	1715-05	2016-12	Expanding	-0.042	0.558	0.003	0.584	0.003	0.209
ma_1_12	1715-05	2016-12	Expanding	-0.084	0.186	-0.018	0.257	0.001	0.057
ma_1_9	1715-05	2016-12	Expanding	-0.084	0.185	-0.009	0.686	0.001	0.063
lag1	1730-05	2016-12	Rolling 240	-0.104	0.312	-0.011	0.394	0.001	0.002
ma_2_9	1730-05	2016-12	Rolling 240	-0.039	0.811	-0.025	0.802	-0.001	0.017
ma_3_9	1715-05	2016-12	Expanding	0.021	0.488	0.006	0.256	-0.002	0.196
return_c_enet	1735-05	2016-12	Rolling 240	0.032	0.434	-0.026	0.805	-0.003	0.319
ma_3_12	1715-05	2016-12	Expanding	-0.006	0.977	0.001	0.702	-0.003	0.109
ma_2_12	1730-05	2016-12	Rolling 240	-0.102	0.676	-0.029	0.764	-0.004	0.015
dy_long	1715-05	2016-12	Expanding	-0.03	0.449	0.02	0.034	-0.007	0.662
return_dmspe	1730-06	2016-12	Rolling 240	-0.074	0.117	-0.009	0.3	-0.009	0.145
return_dmspe	1715-06	2016-12	Rolling 60	-0.068	0.102	-0.01	0.426	-0.009	0.242
return_dmspe	1715-06	2016-12	Expanding	-0.078	0.12	-0.008	0.389	-0.01	0.125
dy_long	1730-05	2016-12	Rolling 240	0.188	0.021	0.007	0.187	-0.011	0.097
ma_1_9	1730-05	2016-12	Rolling 240	0.076	0.079	-0.031	0.271	-0.011	0.04
ma_1_12	1730-05	2016-12	Rolling 240	0.081	0.064	-0.034	0.373	-0.013	0.028
mom9	1730-05	2016-12	Rolling 240	-0.079	0.954	-0.047	0.701	-0.018	0.135
mom12	1730-05	2016-12	Rolling 240	-0.15	0.719	-0.055	0.39	-0.022	0.138

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
mean12	1730-05	2016-12	Rolling 240	0.012	0.656	-0.075	0.92	-0.025	0.312
mean9	1730-05	2016-12	Rolling 240	0.034	0.428	-0.065	0.985	-0.026	0.321
ma_3_9	1730-05	2016-12	Rolling 240	0.068	0.159	-0.04	0.582	-0.028	0.651
lag2	1730-05	2016-12	Rolling 240	-0.008	0.986	-0.04	0.687	-0.028	0.652
dp_long	1730-05	2016-12	Rolling 240	0.216	0.011	-0.008	0.52	-0.03	0.387
ma_3_12	1730-05	2016-12	Rolling 240	0.015	0.578	-0.041	0.289	-0.03	0.995
lag3	1730-05	2016-12	Rolling 240	0.065	0.077	-0.043	0.669	-0.032	0.416
sd	1715-05	2016-12	Expanding	0.003	0.13	0.001	0.689	-0.035	0.067
dp_long	1715-05	2016-12	Expanding	-0.011	0.7	0.009	0.055	-0.039	0.388
kurt	1730-05	2016-12	Rolling 240	0.031	0.444	-0.044	0.706	-0.051	0.704
sd	1730-05	2016-12	Rolling 240	0.079	0.241	-0.086	0.835	-0.071	0.518
lag2	1715-05	2016-12	Expanding	0.004	0.424	-0.025	0.377	-0.077	0.886
return_cmean	1715-05	2016-12	Rolling 60	-0.016	0.504	-0.101	0.864	-0.08	0.588
lag1	1715-05	2016-12	Rolling 60	-0.223	0.88	-0.175	0.484	-0.081	0.163
return_c_enet	1720-05	2016-12	Rolling 60	-0.025	0.539	-0.106	0.799	-0.088	0.882
skew	1730-05	2016-12	Rolling 240	0.052	0.328	-0.166	0.274	-0.098	0.601
mean12	1715-05	2016-12	Expanding	-0.004	0.969	-0.005	0.834	-0.105	0.791
ma_1_9	1715-05	2016-12	Rolling 60	-0.107	0.619	-0.143	0.231	-0.117	0.863
lag3	1715-05	2016-12	Expanding	0.03	0.274	0.007	0.475	-0.118	0.631
ma_1_12	1715-05	2016-12	Rolling 60	-0.106	0.576	-0.152	0.152	-0.123	0.637
ma_2_12	1715-05	2016-12	Rolling 60	-0.014	0.368	-0.135	0.79	-0.123	0.793
mean9	1715-05	2016-12	Expanding	0.013	0.57	-0.001	0.77	-0.124	0.81
ma_2_9	1715-05	2016-12	Rolling 60	0	0.374	-0.152	0.968	-0.132	0.723
ma_3_9	1715-05	2016-12	Rolling 60	-0.135	0.727	-0.111	0.727	-0.136	0.822
mom12	1715-05	2016-12	Rolling 60	-0.021	0.436	-0.149	0.883	-0.136	0.4
ma_3_12	1715-05	2016-12	Rolling 60	-0.105	0.906	-0.143	0.59	-0.142	0.872
mom9	1715-05	2016-12	Rolling 60	-0.178	0.635	-0.187	0.804	-0.158	0.92
skew	1715-05	2016-12	Expanding	0.036	0.134	0.003	0.378	-0.168	0.82
kurt	1715-05	2016-12	Expanding	0.026	0.15	0.001	0.616	-0.174	0.536
dp_long	1715-05	2016-12	Rolling 60	0.029	0.119	-0.244	0.71	-0.222	0.321
dy_long	1715-05	2016-12	Rolling 60	0.003	0.176	-0.244	0.907	-0.253	0.96
lag2	1715-05	2016-12	Rolling 60	-0.245	0.528	-0.219	0.189	-0.286	0.468
lag3	1715-05	2016-12	Rolling 60	-0.123	0.927	-0.084	0.4	-0.298	0.913
mean12	1715-05	2016-12	Rolling 60	-0.12	0.546	-0.215	0.602	-0.337	0.773
mean9	1715-05	2016-12	Rolling 60	-0.119	0.663	-0.188	0.601	-0.35	0.784
kurt	1715-05	2016-12	Rolling 60	0.055	0.168	-0.317	0.905	-0.486	0.436
skew	1715-05	2016-12	Rolling 60	-0.124	0.688	-0.608	0.59	-0.53	0.63

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
sd	1715-05	2016-12	Rolling 60	-0.145	0.51	-0.398	0.863	-0.537	0.485

Panel B: UK OOS Tests 185902:201612

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
ltr	1859-02	2016-12	Expanding	0.245	0.017	0.029	0.019	0.022	0.003
mix_cmean	1859-02	2016-12	Expanding	0.025	0.268	0.011	0.2	0.017	0.005
tms	1859-02	2016-12	Expanding	0.116	0.16	0.006	0.292	0.015	0.02
macro_cmean	1859-02	2016-12	Expanding	0.097	0.009	0.012	0.204	0.015	0.012
macro_c_enet	1864-02	2016-12	Expanding	0.097	0.009	0.012	0.204	0.015	0.013
mix_c_enet	1864-02	2016-12	Expanding	0.079	0.014	0.012	0.183	0.015	0.009
macro_c_enet	1879-02	2016-12	Rolling 240	0.145	0.073	0.009	0.584	0.012	0.233
macro_cmean	1874-02	2016-12	Rolling 240	0.145	0.073	0.009	0.584	0.012	0.23
dy	1859-02	2016-12	Expanding	-0.075	0.329	0.013	0.12	0.008	0.055
mix_c_enet	1879-02	2016-12	Rolling 240	0.071	0.206	-0.005	0.717	0.008	0.119
dfr	1859-02	2016-12	Expanding	0.085	0.031	0.005	0.337	0.006	0.041
mix_cmean	1874-02	2016-12	Rolling 240	0.074	0.196	-0.013	0.948	0.004	0.269
dy	1874-02	2016-12	Rolling 240	0.188	0.021	0.007	0.187	0.003	0.066
dp	1859-02	2016-12	Expanding	-0.016	0.727	0.003	0.481	0.002	0.235
infl	1859-02	2016-12	Expanding	0.054	0.136	0.001	0.731	0.001	0.349
ltr	1874-02	2016-12	Rolling 240	0.158	0.054	-0.005	0.128	0	0.052
tbl	1859-02	2016-12	Expanding	0.091	0.134	-0.025	0.875	-0.004	0.514
dfy	1859-02	2016-12	Expanding	-0.058	0.314	-0.018	0.409	-0.005	0.185
macro_dmspe	1874-03	2016-12	Rolling 240	-0.045	0.172	-0.005	0.695	-0.005	0.515
macro_dmspe	1859-03	2016-12	Expanding	-0.06	0.178	-0.006	0.466	-0.007	0.182
dp	1874-02	2016-12	Rolling 240	0.216	0.011	-0.008	0.52	-0.008	0.183
macro_dmspe	1859-03	2016-12	Rolling 60	-0.033	0.158	-0.008	0.683	-0.009	0.497
mix_dmspe	1874-03	2016-12	Rolling 240	-0.075	0.126	-0.009	0.339	-0.01	0.129
mix_dmspe	1859-03	2016-12	Rolling 60	-0.071	0.115	-0.009	0.392	-0.01	0.163
mix_dmspe	1859-03	2016-12	Expanding	-0.079	0.128	-0.009	0.368	-0.01	0.103
lty	1859-02	2016-12	Expanding	0.046	0.14	-0.036	0.736	-0.022	0.872
dfy	1874-02	2016-12	Rolling 240	-0.008	0.202	-0.033	0.18	-0.022	0.083
dfr	1874-02	2016-12	Rolling 240	0.163	0.03	-0.042	0.622	-0.024	0.583
tbl	1874-02	2016-12	Rolling 240	0.081	0.224	-0.059	0.811	-0.043	0.476
tms	1874-02	2016-12	Rolling 240	0.08	0.23	-0.061	0.816	-0.045	0.381
lty	1874-02	2016-12	Rolling 240	-0.031	0.583	-0.085	0.903	-0.066	0.856
infl	1874-02	2016-12	Rolling 240	-0.124	0.79	-0.102	0.95	-0.071	0.846
mix_cmean	1859-02	2016-12	Rolling 60	0.033	0.306	-0.089	0.927	-0.077	0.784
mix_c_enet	1864-02	2016-12	Rolling 60	0.004	0.386	-0.087	0.943	-0.082	0.834
macro_cmean	1859-02	2016-12	Rolling 60	0.087	0.162	-0.085	0.973	-0.087	0.842

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
macro_c_enet	1864-02	2016-12	Rolling 60	0.087	0.162	-0.085	0.973	-0.088	0.841
dfr	1859-02	2016-12	Rolling 60	-0.005	0.165	-0.134	0.536	-0.133	0.925
ltr	1859-02	2016-12	Rolling 60	-0.072	0.27	-0.134	0.957	-0.147	0.807
dfy	1859-02	2016-12	Rolling 60	-0.064	0.588	-0.185	0.804	-0.188	0.709
infl	1859-02	2016-12	Rolling 60	-0.254	0.25	-0.248	0.951	-0.205	0.735
tms	1859-02	2016-12	Rolling 60	-0.218	0.626	-0.197	0.78	-0.233	0.952
dy	1859-02	2016-12	Rolling 60	0.003	0.176	-0.244	0.907	-0.243	0.903
lty	1859-02	2016-12	Rolling 60	-0.179	0.355	-0.277	0.758	-0.244	0.468
dp	1859-02	2016-12	Rolling 60	0.029	0.119	-0.244	0.71	-0.245	0.681
tbl	1859-02	2016-12	Rolling 60	0.021	0.229	-0.2	0.696	-0.33	0.851

Panel C: US OOS Tests 186302:202012

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
return_cmean	1863-02	2020-12	Expanding	-0.011	0.85	0.007	0.299	0.039	0.001
lag1	1863-02	2020-12	Expanding	-0.085	0.881	-0.036	0.525	0.036	0.004
ma_2_12	1863-02	2020-12	Expanding	-0.038	0.998	-0.019	0.397	0.026	0
mom12	1863-02	2020-12	Expanding	-0.08	0.465	0.01	0.171	0.025	0.001
mom9	1863-02	2020-12	Expanding	-0.078	0.518	0.011	0.163	0.025	0.003
ma_1_12	1863-02	2020-12	Expanding	0.007	0.676	-0.02	0.552	0.02	0.001
ma_2_9	1863-02	2020-12	Expanding	-0.082	0.577	-0.044	0.978	0.02	0.001
return_cmean	1878-02	2020-12	Rolling 240	0.008	0.701	-0.023	0.647	0.018	0.106
sd	1863-02	2020-12	Expanding	0.044	0.137	0.01	0.181	0.016	0.002
lag1	1878-02	2020-12	Rolling 240	-0.063	0.848	-0.054	0.409	0.015	0.011
ma_1_9	1863-02	2020-12	Expanding	0.001	0.753	-0.013	0.547	0.015	0.001
return_c_enet	1868-02	2020-12	Expanding	-0.013	0.918	0.008	0.259	0.015	0.043
ma_2_9	1878-02	2020-12	Rolling 240	-0.026	0.692	-0.04	0.362	0.014	0.009
mean9	1863-02	2020-12	Expanding	-0.034	0.577	-0.022	0.824	0.013	0.113
ma_1_12	1878-02	2020-12	Rolling 240	0.008	0.68	-0.035	0.759	0.009	0.005
ma_2_12	1878-02	2020-12	Rolling 240	-0.029	0.89	-0.034	0.421	0.008	0.01
mean12	1863-02	2020-12	Expanding	-0.041	0.442	-0.007	0.591	0.008	0.192
ma_1_9	1878-02	2020-12	Rolling 240	0.012	0.54	-0.027	0.649	0.004	0.008
lag3	1878-02	2020-12	Rolling 240	-0.091	0.452	-0.032	0.751	0.003	0.095
mom12	1878-02	2020-12	Rolling 240	-0.068	0.491	-0.042	0.687	0.001	0.041
mom9	1878-02	2020-12	Rolling 240	-0.075	0.658	-0.038	0.745	0	0.066
skew	1863-02	2020-12	Expanding	-0.004	0.279	0.001	0.646	-0.005	0.906
ma_3_9	1863-02	2020-12	Expanding	-0.027	0.256	-0.002	0.937	-0.005	0.283
ma_3_12	1863-02	2020-12	Expanding	-0.02	0.232	-0.004	0.654	-0.006	0.359
return_c_enet	1883-02	2020-12	Rolling 240	0.016	0.566	-0.022	0.759	-0.007	0.125
lag3	1863-02	2020-12	Expanding	0.023	0.505	-0.043	0.357	-0.007	0.402
return_dmspe	1863-03	2020-12	Rolling 60	-0.068	0.161	-0.025	0.16	-0.011	0.173
return_dmspe	1863-03	2020-12	Expanding	-0.082	0.159	-0.026	0.148	-0.011	0.157
ma_3_9	1878-02	2020-12	Rolling 240	0.008	0.637	-0.035	0.284	-0.013	0.202
ma_3_12	1878-02	2020-12	Rolling 240	-0.019	0.747	-0.044	0.145	-0.015	0.217
lag2	1863-02	2020-12	Expanding	0	0.814	-0.003	0.223	-0.018	0.26
mean9	1878-02	2020-12	Rolling 240	-0.015	0.946	-0.052	0.71	-0.018	0.296
return_dmspe	1878-03	2020-12	Rolling 240	-0.08	0.149	-0.027	0.108	-0.025	0.048
kurt	1863-02	2020-12	Expanding	0.044	0.166	0.004	0.316	-0.033	0.909
mean12	1878-02	2020-12	Rolling 240	-0.026	0.822	-0.053	0.666	-0.034	0.552

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
lag2	1878-02	2020-12	Rolling 240	0.058	0.165	-0.024	0.604	-0.04	0.772
return_cmean	1863-02	2020-12	Rolling 60	0.109	0.166	-0.054	0.642	-0.052	0.343
return_c_enet	1868-02	2020-12	Rolling 60	0.082	0.225	-0.058	0.766	-0.065	0.39
mom12	1863-02	2020-12	Rolling 60	0.257	0.077	-0.067	0.174	-0.072	0.055
lag1	1863-02	2020-12	Rolling 60	-0.152	0.984	-0.158	0.964	-0.073	0.015
ma_2_9	1863-02	2020-12	Rolling 60	0.044	0.324	-0.136	0.959	-0.087	0.156
skew	1878-02	2020-12	Rolling 240	0.075	0.258	-0.046	0.617	-0.1	0.718
ma_2_12	1863-02	2020-12	Rolling 60	-0.034	0.51	-0.121	0.728	-0.102	0.425
mom9	1863-02	2020-12	Rolling 60	0.182	0.166	-0.111	0.748	-0.116	0.367
sd	1878-02	2020-12	Rolling 240	-0.215	0.029	-0.06	0.756	-0.116	0.807
ma_1_12	1863-02	2020-12	Rolling 60	-0.045	0.633	-0.121	0.865	-0.118	0.668
ma_1_9	1863-02	2020-12	Rolling 60	-0.036	0.584	-0.135	0.455	-0.124	0.879
ma_3_9	1863-02	2020-12	Rolling 60	0.067	0.216	-0.123	0.631	-0.134	0.644
lag3	1863-02	2020-12	Rolling 60	-0.044	0.375	-0.144	0.546	-0.139	0.242
ma_3_12	1863-02	2020-12	Rolling 60	0.093	0.215	-0.125	0.913	-0.144	0.758
lag2	1863-02	2020-12	Rolling 60	0.04	0.371	-0.148	0.421	-0.173	0.525
mean9	1863-02	2020-12	Rolling 60	0.127	0.166	-0.184	0.692	-0.177	0.674
kurt	1878-02	2020-12	Rolling 240	0.208	0.116	-0.069	0.427	-0.183	0.757
mean12	1863-02	2020-12	Rolling 60	0.23	0.06	-0.167	0.581	-0.199	0.811
skew	1863-02	2020-12	Rolling 60	-0.186	0.374	-0.257	0.389	-0.248	0.328
sd	1863-02	2020-12	Rolling 60	0.005	0.605	-0.156	0.274	-0.31	0.518
kurt	1863-02	2020-12	Rolling 60	0.03	0.255	-0.193	0.165	-0.332	0.686

Panel D: US OOS Tests 193102-202012

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
macro_c_enet	1951-02	2020-12	Rolling 240	0.074	0.175	0.022	0.067	0.04	0.001
macro_cmean	1946-02	2020-12	Rolling 240	0.072	0.049	0.015	0.157	0.027	0.008
mix_c_enet	1936-02	2020-12	Expanding	0.04	0.211	0.016	0.08	0.025	0.01
infl	1946-02	2020-12	Rolling 240	0.207	0.018	0.005	0.106	0.011	0.017
mix_cmean	1946-02	2020-12	Rolling 240	0.032	0.349	-0.007	0.731	0.01	0.037
mix_c_enet	1951-02	2020-12	Rolling 240	0.027	0.433	-0.006	0.607	0.009	0.023
mix_cmean	1931-02	2020-12	Expanding	0.02	0.401	0.014	0.068	0.006	0.606
macro_c_enet	1936-02	2020-12	Expanding	0.063	0.118	0.02	0.043	0.003	0.215
lty	1946-02	2020-12	Rolling 240	0.172	0.14	-0.034	0.36	-0.009	0.051
macro_dmspe	1931-03	2020-12	Rolling 60	-0.06	0.129	-0.018	0.41	-0.01	0.49
macro_dmspe	1931-03	2020-12	Expanding	-0.066	0.17	-0.02	0.166	-0.011	0.281
mix_dmspe	1931-03	2020-12	Rolling 60	-0.076	0.157	-0.026	0.156	-0.012	0.123
mix_dmspe	1931-03	2020-12	Expanding	-0.083	0.16	-0.027	0.141	-0.012	0.118
ltr	1946-02	2020-12	Rolling 240	0.007	0.793	-0.021	0.21	-0.014	0.028
macro_dmspe	1946-03	2020-12	Rolling 240	-0.066	0.191	-0.02	0.225	-0.017	0.175
tms	1946-02	2020-12	Rolling 240	-0.005	0.981	-0.02	0.069	-0.02	0.015
dp	1946-02	2020-12	Rolling 240	-0.047	0.596	-0.048	0.832	-0.023	0.287
dy	1946-02	2020-12	Rolling 240	-0.091	0.533	-0.055	0.794	-0.025	0.249
mix_dmspe	1946-03	2020-12	Rolling 240	-0.082	0.156	-0.028	0.119	-0.027	0.045
macro_cmean	1931-02	2020-12	Expanding	0.069	0.109	0.021	0.038	-0.03	0.962
lty	1931-02	2020-12	Expanding	0.109	0.129	-0.016	0.465	-0.034	0.493
macro_c_enet	1936-02	2020-12	Rolling 60	-0.064	0.656	-0.076	0.629	-0.048	0.064
mix_c_enet	1936-02	2020-12	Rolling 60	0.041	0.339	-0.065	0.822	-0.049	0.142
dfy	1946-02	2020-12	Rolling 240	-0.013	0.873	-0.062	0.675	-0.051	0.334
infl	1931-02	2020-12	Expanding	0.076	0.115	0.014	0.104	-0.053	0.881
tbl	1931-02	2020-12	Expanding	0.113	0.092	0.008	0.165	-0.054	0.988
dfr	1931-02	2020-12	Expanding	0.018	0.698	0.011	0.239	-0.054	0.853
tbl	1946-02	2020-12	Rolling 240	0.127	0.046	-0.023	0.257	-0.056	0.164
tms	1931-02	2020-12	Expanding	0.034	0.106	0.009	0.083	-0.056	0.903
ltr	1931-02	2020-12	Expanding	0.065	0.43	0.015	0.1	-0.061	0.984
dfr	1946-02	2020-12	Rolling 240	-0.076	0.841	-0.1	0.138	-0.061	0.865
mix_cmean	1931-02	2020-12	Rolling 60	0.08	0.21	-0.04	0.497	-0.066	0.73
dp	1931-02	2020-12	Expanding	0.041	0.201	-0.002	0.759	-0.073	0.683
macro_cmean	1931-02	2020-12	Rolling 60	0.021	0.4	-0.032	0.337	-0.09	0.852
dy	1931-02	2020-12	Expanding	0.035	0.208	-0.003	0.958	-0.095	0.434

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
lty	1931-02	2020-12	Rolling 60	-0.029	0.238	-0.186	0.403	-0.147	0.527
ltr	1931-02	2020-12	Rolling 60	-0.096	0.835	-0.128	0.878	-0.164	0.919
dfy	1931-02	2020-12	Expanding	0.075	0.112	0.008	0.229	-0.167	0.779
tbl	1931-02	2020-12	Rolling 60	-0.157	0.913	-0.176	0.695	-0.18	0.585
tms	1931-02	2020-12	Rolling 60	-0.071	0.503	-0.16	0.512	-0.183	0.91
infl	1931-02	2020-12	Rolling 60	0.065	0.163	-0.141	0.409	-0.185	0.429
dfr	1931-02	2020-12	Rolling 60	-0.455	0.394	-0.191	0.633	-0.189	0.921
dp	1931-02	2020-12	Rolling 60	-0.062	0.892	-0.186	0.495	-0.254	0.681
dfy	1931-02	2020-12	Rolling 60	0.23	0.043	-0.097	0.033	-0.301	0.503
dy	1931-02	2020-12	Rolling 60	-0.042	0.936	-0.214	0.627	-0.307	0.447

Table 4: Economic Gains: in 300 Years

Table 4 presents the economic gains according to the certainty equivalent return (CER). I calculate the difference between the CER of the alternative predictions and the CER of the null prediction by the expanding mean of equity premium. I also report the relative turnover, which is the turnover of the alternative predictions divided by the turnover of the null prediction. Panel A and B report the economic gains for the UK market. Panel C and D report the economic gains for the US market. The CER gains are annualized.

Panel A: UK Economic Gains 171505-201612

Predictor	Start	End	Update	CER Gains	Relative Turnover
return_c_enet	1720-05	2016-12	Expanding	1.213	20.712
return_dmspe	1715-06	2016-12	Expanding	1.107	2.995
return_dmspe	1730-06	2016-12	Rolling 240	1.094	3.04
return_dmspe	1715-06	2016-12	Rolling 60	1.03	3.413
ma_2_9	1715-05	2016-12	Expanding	0.862	9.706
ma_2_12	1715-05	2016-12	Expanding	0.858	8.072
return_cmean	1715-05	2016-12	Expanding	0.645	18.113
lag1	1715-05	2016-12	Expanding	0.54	43.665
ma_2_12	1730-05	2016-12	Rolling 240	0.317	9.04
mom12	1715-05	2016-12	Expanding	0.228	4.312
ma_2_9	1730-05	2016-12	Rolling 240	0.167	9.421
ma_1_12	1715-05	2016-12	Expanding	0.061	35.613
mom9	1715-05	2016-12	Expanding	0.058	6.735
ma_1_9	1715-05	2016-12	Expanding	0.052	34.125
lag1	1730-05	2016-12	Rolling 240	0.016	36.366
kurt	1715-05	2016-12	Expanding	-0.059	0.63
return_cmean	1730-05	2016-12	Rolling 240	-0.101	12.582
skew	1715-05	2016-12	Expanding	-0.196	0.743
mean12	1730-05	2016-12	Rolling 240	-0.205	7.558
lag2	1715-05	2016-12	Expanding	-0.32	31.368
mean9	1730-05	2016-12	Rolling 240	-0.375	8.425
ma_3_9	1715-05	2016-12	Expanding	-0.378	19.839
lag3	1715-05	2016-12	Expanding	-0.409	12.951
mean9	1715-05	2016-12	Expanding	-0.421	5.276
return_c_enet	1735-05	2016-12	Rolling 240	-0.464	13.957
ma_3_12	1715-05	2016-12	Expanding	-0.465	19.497
mom9	1730-05	2016-12	Rolling 240	-0.624	8.215
ma_1_12	1730-05	2016-12	Rolling 240	-0.662	31.918
mean12	1715-05	2016-12	Expanding	-0.686	4.968

Predictor	Start	End	Update	CER Gains	Relative Turnover
ma_1_9	1730-05	2016-12	Rolling 240	-0.751	29.953
return_c_enet	1720-05	2016-12	Rolling 60	-0.815	12.523
mom12	1730-05	2016-12	Rolling 240	-0.859	6.945
dy_long	1715-05	2016-12	Expanding	-0.944	2.028
kurt	1730-05	2016-12	Rolling 240	-1.046	4.237
dp_long	1715-05	2016-12	Expanding	-1.072	2.273
dp_long	1730-05	2016-12	Rolling 240	-1.175	6.175
return_cmean	1715-05	2016-12	Rolling 60	-1.189	10.278
ma_2_12	1715-05	2016-12	Rolling 60	-1.214	7.697
lag1	1715-05	2016-12	Rolling 60	-1.216	25.243
skew	1715-05	2016-12	Rolling 60	-1.224	6.372
ma_3_9	1730-05	2016-12	Rolling 240	-1.249	16.608
lag2	1730-05	2016-12	Rolling 240	-1.264	24.928
ma_1_12	1715-05	2016-12	Rolling 60	-1.279	25.5
dy_long	1730-05	2016-12	Rolling 240	-1.319	5.922
kurt	1715-05	2016-12	Rolling 60	-1.353	7.195
mom12	1715-05	2016-12	Rolling 60	-1.413	8.604
lag3	1730-05	2016-12	Rolling 240	-1.418	22.032
ma_2_9	1715-05	2016-12	Rolling 60	-1.438	10.035
sd	1730-05	2016-12	Rolling 240	-1.49	4.081
skew	1730-05	2016-12	Rolling 240	-1.496	4.073
ma_1_9	1715-05	2016-12	Rolling 60	-1.547	25.706
mean9	1715-05	2016-12	Rolling 60	-1.608	8.545
ma_3_12	1730-05	2016-12	Rolling 240	-1.613	15.12
mom9	1715-05	2016-12	Rolling 60	-1.618	9.35
lag2	1715-05	2016-12	Rolling 60	-1.637	21.342
mean12	1715-05	2016-12	Rolling 60	-1.684	8.542
sd	1715-05	2016-12	Rolling 60	-1.764	7.753
dp_long	1715-05	2016-12	Rolling 60	-1.805	12.516
dy_long	1715-05	2016-12	Rolling 60	-1.864	7.769
ma_3_9	1715-05	2016-12	Rolling 60	-1.903	15.805
ma_3_12	1715-05	2016-12	Rolling 60	-1.923	14.679
sd	1715-05	2016-12	Expanding	-2.656	0.739
lag3	1715-05	2016-12	Rolling 60	-2.664	20.167

Panel B: UK Economic Gains 185902-201612

Predictor	Start	End	Update	CER Gains	Relative Turnover
macro_dmspe	1874-03	2016-12	Rolling 240	1.181	4.773
mix_dmspe	1874-03	2016-12	Rolling 240	1.097	1.905
mix_dmspe	1859-03	2016-12	Expanding	1.086	1.926
mix_dmspe	1859-03	2016-12	Rolling 60	1.044	2.177
macro_dmspe	1859-03	2016-12	Rolling 60	0.978	6.118
macro_dmspe	1859-03	2016-12	Expanding	0.848	3.8
mix_cmean	1859-02	2016-12	Expanding	0.683	12.448
lty	1859-02	2016-12	Rolling 60	0.19	10.526
tbl	1859-02	2016-12	Expanding	0.045	3.906
ltr	1859-02	2016-12	Expanding	-0.008	35.226
dp	1859-02	2016-12	Expanding	-0.03	4.699
tbl	1874-02	2016-12	Rolling 240	-0.218	11.127
macro_c_enet	1879-02	2016-12	Rolling 240	-0.239	11.571
dy	1859-02	2016-12	Expanding	-0.241	3.129
dp	1874-02	2016-12	Rolling 240	-0.269	8.002
macro_cmean	1874-02	2016-12	Rolling 240	-0.272	10.011
tms	1859-02	2016-12	Expanding	-0.274	4.717
mix_cmean	1874-02	2016-12	Rolling 240	-0.284	11.244
tbl	1859-02	2016-12	Rolling 60	-0.325	13.553
mix_c_enet	1864-02	2016-12	Expanding	-0.344	5.931
macro_c_enet	1864-02	2016-12	Expanding	-0.349	7.072
macro_cmean	1859-02	2016-12	Expanding	-0.362	7.18
dy	1874-02	2016-12	Rolling 240	-0.466	5.992
macro_c_enet	1864-02	2016-12	Rolling 60	-0.476	12.03
mix_c_enet	1879-02	2016-12	Rolling 240	-0.479	12.317
mix_cmean	1859-02	2016-12	Rolling 60	-0.506	11.682
macro_cmean	1859-02	2016-12	Rolling 60	-0.507	12.004
lty	1874-02	2016-12	Rolling 240	-0.646	6.18
lty	1859-02	2016-12	Expanding	-0.678	2.779
tms	1874-02	2016-12	Rolling 240	-0.732	11.775
mix_c_enet	1864-02	2016-12	Rolling 60	-0.805	12.459
dfr	1859-02	2016-12	Expanding	-0.846	4.955
infl	1859-02	2016-12	Expanding	-0.941	2.165
ltr	1874-02	2016-12	Rolling 240	-0.945	33.706
dp	1859-02	2016-12	Rolling 60	-1.036	12.299

Predictor	Start	End	Update	CER Gains	Relative Turnover
tms	1859-02	2016-12	Rolling 60	-1.211	15.123
dfy	1874-02	2016-12	Rolling 240	-1.213	10.739
infl	1859-02	2016-12	Rolling 60	-1.255	12
infl	1874-02	2016-12	Rolling 240	-1.361	5.285
dy	1859-02	2016-12	Rolling 60	-1.461	11.152
dfr	1874-02	2016-12	Rolling 240	-1.479	15.43
dfy	1859-02	2016-12	Rolling 60	-1.619	14.8
dfr	1859-02	2016-12	Rolling 60	-1.965	18.846
ltr	1859-02	2016-12	Rolling 60	-2.265	28.56
dfy	1859-02	2016-12	Expanding	-2.27	5.65

Panel C: US Economic Gains 186302-202012

Predictor	Start	End	Update	CER Gains	Relative Turnover
lag1	1863-02	2020-12	Expanding	2.837	49.675
mean12	1863-02	2020-12	Expanding	2.701	9.533
ma_2_12	1863-02	2020-12	Expanding	2.614	10.935
return_cmean	1863-02	2020-12	Expanding	2.388	17.932
mom12	1863-02	2020-12	Expanding	2.374	8.221
ma_1_12	1863-02	2020-12	Expanding	2.337	48.175
return_c_enet	1868-02	2020-12	Expanding	2.336	10.371
lag1	1863-02	2020-12	Rolling 60	2.325	30.927
mean9	1863-02	2020-12	Expanding	2.316	11.372
mom9	1863-02	2020-12	Expanding	2.249	8.798
lag1	1878-02	2020-12	Rolling 240	2.191	37.703
ma_2_9	1863-02	2020-12	Expanding	2.12	12.67
ma_1_9	1863-02	2020-12	Expanding	1.873	46.509
ma_2_12	1878-02	2020-12	Rolling 240	1.861	8.578
mom9	1878-02	2020-12	Rolling 240	1.693	9.661
mean12	1878-02	2020-12	Rolling 240	1.663	8.41
mom12	1878-02	2020-12	Rolling 240	1.657	8.288
return_cmean	1878-02	2020-12	Rolling 240	1.655	12.369
ma_2_9	1878-02	2020-12	Rolling 240	1.504	10.82
ma_1_12	1878-02	2020-12	Rolling 240	1.467	37.092
mean9	1878-02	2020-12	Rolling 240	1.448	10.979
sd	1878-02	2020-12	Rolling 240	1.312	2.68
return_cmean	1863-02	2020-12	Rolling 60	1.266	12.186
sd	1863-02	2020-12	Expanding	1.204	1.058
mean9	1863-02	2020-12	Rolling 60	1.187	9.958
mom12	1863-02	2020-12	Rolling 60	1.095	8.92
kurt	1863-02	2020-12	Expanding	1.079	1.761
mom9	1863-02	2020-12	Rolling 60	1.076	10.888
ma_2_9	1863-02	2020-12	Rolling 60	1.044	12.191
ma_2_12	1863-02	2020-12	Rolling 60	1.022	10.276
ma_1_9	1878-02	2020-12	Rolling 240	0.993	32.444
kurt	1863-02	2020-12	Rolling 60	0.987	9.571
return_c_enet	1883-02	2020-12	Rolling 240	0.986	5.516
mean12	1863-02	2020-12	Rolling 60	0.709	8.385
return_c_enet	1868-02	2020-12	Rolling 60	0.661	12.251

Predictor	Start	End	Update	CER Gains	Relative Turnover
skew	1863-02	2020-12	Expanding	0.636	1.368
skew	1878-02	2020-12	Rolling 240	0.493	3.918
ma_1_12	1863-02	2020-12	Rolling 60	0.286	27.259
ma_3_12	1878-02	2020-12	Rolling 240	0.277	14.959
ma_3_12	1863-02	2020-12	Expanding	0.271	16.826
lag3	1878-02	2020-12	Rolling 240	0.266	21.208
ma_3_9	1863-02	2020-12	Expanding	0.252	19.051
ma_3_9	1878-02	2020-12	Rolling 240	0.244	14.336
ma_1_9	1863-02	2020-12	Rolling 60	0.24	23.651
ma_3_12	1863-02	2020-12	Rolling 60	0.168	15.517
sd	1863-02	2020-12	Rolling 60	0.127	8.829
kurt	1878-02	2020-12	Rolling 240	0.097	4.452
lag3	1863-02	2020-12	Rolling 60	-0.215	23.558
ma_3_9	1863-02	2020-12	Rolling 60	-0.216	14.908
skew	1863-02	2020-12	Rolling 60	-0.223	9.935
lag2	1863-02	2020-12	Expanding	-0.227	7.004
lag2	1878-02	2020-12	Rolling 240	-0.348	13.638
lag3	1863-02	2020-12	Expanding	-0.449	28.024
lag2	1863-02	2020-12	Rolling 60	-0.48	19.809
return_dmspe	1863-03	2020-12	Rolling 60	-0.845	1.272
return_dmspe	1863-03	2020-12	Expanding	-1.161	1.134
return_dmspe	1878-03	2020-12	Rolling 240	-1.225	0.667

Panel D: US Economic Gains 193102-202012

Predictor	Start	End	Update	CER Gains	Relative Turnover
macro_c_enet	1951-02	2020-12	Rolling 240	2.822	9.076
tms	1946-02	2020-12	Rolling 240	2.399	5.271
infl	1946-02	2020-12	Rolling 240	2.143	3.317
mix_c_enet	1936-02	2020-12	Expanding	2.047	6.839
mix_cmean	1931-02	2020-12	Expanding	2.032	12.491
macro_cmean	1946-02	2020-12	Rolling 240	2.011	6.166
tbl	1931-02	2020-12	Expanding	1.941	2.688
lty	1946-02	2020-12	Rolling 240	1.899	2.513
tms	1931-02	2020-12	Expanding	1.882	4.165
dfy	1931-02	2020-12	Rolling 60	1.827	11.447
macro_cmean	1931-02	2020-12	Expanding	1.767	5.128
macro_c_enet	1936-02	2020-12	Rolling 60	1.656	13.752
infl	1931-02	2020-12	Rolling 60	1.626	9.027
macro_c_enet	1936-02	2020-12	Expanding	1.555	8.326
mix_c_enet	1951-02	2020-12	Rolling 240	1.439	6.37
lty	1931-02	2020-12	Expanding	1.395	3.045
macro_cmean	1931-02	2020-12	Rolling 60	1.328	12.128
mix_cmean	1946-02	2020-12	Rolling 240	1.304	5.921
dy	1946-02	2020-12	Rolling 240	1.147	5.586
tbl	1946-02	2020-12	Rolling 240	1.143	3.204
lty	1931-02	2020-12	Rolling 60	1.129	11.596
mix_c_enet	1936-02	2020-12	Rolling 60	1.089	12.302
mix_cmean	1931-02	2020-12	Rolling 60	1.078	10.604
infl	1931-02	2020-12	Expanding	1.057	2.457
dfy	1931-02	2020-12	Expanding	0.964	2.293
ltr	1946-02	2020-12	Rolling 240	0.908	23.905
tbl	1931-02	2020-12	Rolling 60	0.866	9.426
dfy	1946-02	2020-12	Rolling 240	0.794	7.153
dp	1946-02	2020-12	Rolling 240	0.78	4.339
tms	1931-02	2020-12	Rolling 60	0.748	9.469
dfr	1931-02	2020-12	Rolling 60	0.524	27.053
dfr	1931-02	2020-12	Expanding	0.497	19.304
ltr	1931-02	2020-12	Expanding	0.425	27.79
dp	1931-02	2020-12	Expanding	0.33	2.054
ltr	1931-02	2020-12	Rolling 60	0.272	24.799

Predictor	Start	End	Update	CER Gains	Relative Turnover
dfr	1946-02	2020-12	Rolling 240	0.047	19.326
dy	1931-02	2020-12	Expanding	-0.046	2.772
dp	1931-02	2020-12	Rolling 60	-0.205	9.047
dy	1931-02	2020-12	Rolling 60	-0.26	11.797
macro_dmspe	1931-03	2020-12	Rolling 60	-0.321	2.706
macro_dmspe	1946-03	2020-12	Rolling 240	-0.709	1.191
macro_dmspe	1931-03	2020-12	Expanding	-0.796	0.86
mix_dmspe	1931-03	2020-12	Rolling 60	-1.034	0.776
mix_dmspe	1931-03	2020-12	Expanding	-1.236	0.61
mix_dmspe	1946-03	2020-12	Rolling 240	-1.38	0.423

Table 5: Out-of-Sample Tests: Transfer Learning

Table 5 reports the out-of-sample (OOS) test results for the transfer learning setups. The transfer learning setups fit the models with the UK market and apply the parameters to make one-period-ahead predictions in the US market. Panel A shows the transfer learning predictability for the period 1863-2017 mainly focusing on technical indicators. Panel B shows the results for the period 193102-201701 mainly focusing on macroeconomic predictors. The column “update” indicates the model updating scheme, including expanding window update using all past observations, 60-month rolling window using past 60 months and 240-month rolling window update using past 240 months. The column “last 50 year” shows the OOS R^2 for the last 50 years in the sample and the column “last 5 year” shows the OOS R^2 for the last 5 years in the sample. The “all year” column shows the OOS R^2 for the entire sample. The p values to the right of the testing windows are from the Clark and West test. The OOS R^2s are annualized.

Panel A: Transfer Learning US OOS Tests 186302-201701

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
lag1	1858-02	2017-01	Rolling 240	-0.031	0.836	-0.028	0.595	0.073	0
lag1	1858-02	2017-01	Expanding	-0.211	0.363	-0.059	0.416	0.059	0.001
ma_1_12	1858-02	2017-01	Rolling 240	0.041	0.294	-0.008	0.626	0.046	0
ma_2_12	1858-02	2017-01	Expanding	0.001	0.769	-0.001	0.529	0.04	0
return_cmean	1858-02	2017-01	Expanding	-0.058	0.108	0.003	0.637	0.04	0
mom9	1858-02	2017-01	Expanding	-0.037	0.681	0.008	0.38	0.039	0
ma_2_9	1858-02	2017-01	Expanding	0.004	0.737	-0.01	0.858	0.039	0
ma_1_12	1858-02	2017-01	Expanding	-0.098	0.175	0	0.57	0.038	0
ma_1_9	1858-02	2017-01	Rolling 240	0.031	0.407	-0.007	0.721	0.038	0
mom12	1858-02	2017-01	Rolling 240	-0.073	0.876	-0.028	0.868	0.038	0.003
ma_2_9	1858-02	2017-01	Rolling 240	-0.012	0.727	-0.046	0.821	0.038	0
mom9	1858-02	2017-01	Rolling 240	0.016	0.604	-0.044	0.734	0.035	0.003
mom12	1858-02	2017-01	Expanding	-0.066	0.2	0.006	0.427	0.034	0.001
ma_1_9	1858-02	2017-01	Expanding	-0.091	0.206	-0.003	0.723	0.034	0.001
ma_2_12	1858-02	2017-01	Rolling 240	-0.02	0.818	-0.029	0.854	0.033	0.001
mean12	1858-02	2017-01	Expanding	0.001	0.874	-0.003	0.746	0.032	0.008
mean9	1858-02	2017-01	Expanding	0	0.91	-0.008	0.988	0.032	0.007
skew	1858-02	2017-01	Expanding	0.003	0.042	0.005	0.117	0.02	0.02
ma_3_9	1858-02	2017-01	Expanding	-0.154	0.008	-0.005	0.916	0.019	0.016
kurt	1858-02	2017-01	Expanding	0.023	0.026	0.004	0.177	0.019	0.029
mean9	1858-02	2017-01	Rolling 240	0.062	0.191	-0.076	0.636	0.019	0.052
ma_3_12	1858-02	2017-01	Expanding	-0.116	0.024	-0.009	0.568	0.018	0.018
ma_3_9	1858-02	2017-01	Rolling 240	-0.169	0.034	-0.04	0.898	0.017	0.006
ma_3_12	1858-02	2017-01	Rolling 240	-0.03	0.292	-0.045	0.404	0.016	0.011
return_dmspe	1858-03	2017-01	Rolling 240	0.125	0.071	-0.004	0.521	0.014	0.054

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
mean12	1858-02	2017-01	Rolling 240	0.048	0.254	-0.078	0.593	0.012	0.058
ma_1_12	1858-02	2017-01	Rolling 60	0.062	0.228	-0.113	0.868	0.01	0.001
return_c_enet	1863-02	2017-01	Expanding	-0.038	0.225	0.006	0.423	0.008	0.122
lag2	1858-02	2017-01	Rolling 240	0.001	0.869	-0.022	0.814	0.006	0.045
lag3	1858-02	2017-01	Expanding	-0.073	0.035	-0.004	0.781	0.003	0.226
lag2	1858-02	2017-01	Expanding	-0.059	0.044	-0.012	0.444	-0.001	0.244
ma_1_9	1858-02	2017-01	Rolling 60	0.036	0.285	-0.126	0.802	-0.006	0.009
return_dmspe	1858-03	2017-01	Expanding	-0.17	0.033	-0.02	0.352	-0.009	0.332
lag1	1858-02	2017-01	Rolling 60	0.067	0.196	-0.168	0.69	-0.009	0.004
sd	1858-02	2017-01	Expanding	-0.266	0.032	-0.041	0.315	-0.013	0.43
ma_2_9	1858-02	2017-01	Rolling 60	0.036	0.372	-0.181	0.625	-0.023	0.012
ma_2_12	1858-02	2017-01	Rolling 60	0.076	0.293	-0.153	0.854	-0.024	0.039
mom12	1858-02	2017-01	Rolling 60	0.297	0.055	-0.139	0.286	-0.025	0.005
ma_3_12	1858-02	2017-01	Rolling 60	-0.033	0.622	-0.178	0.954	-0.032	0.061
ma_3_9	1858-02	2017-01	Rolling 60	-0.359	0.287	-0.201	0.931	-0.044	0.083
lag2	1858-02	2017-01	Rolling 60	-0.114	0.978	-0.176	0.342	-0.045	0.106
mom9	1858-02	2017-01	Rolling 60	0.086	0.283	-0.29	0.815	-0.05	0.061
lag3	1858-02	2017-01	Rolling 60	-0.026	0.58	-0.152	0.993	-0.08	0.513
lag3	1858-02	2017-01	Rolling 240	-0.009	0.874	-0.076	0.702	-0.08	0.624
mean12	1858-02	2017-01	Rolling 60	0.163	0.164	-0.251	0.454	-0.091	0.123
mean9	1858-02	2017-01	Rolling 60	0.147	0.159	-0.194	0.488	-0.111	0.251
return_cmean	1858-02	2017-01	Rolling 240	-0.095	0.055	-0.105	0.307	-0.164	0.017
kurt	1858-02	2017-01	Rolling 240	-2.691	0.13	-1.892	0.927	-4.377	0.064
return_dmspe	1858-03	2017-01	Rolling 60	-49.084	0.335	-6.518	0.55	-4.429	0.981
skew	1858-02	2017-01	Rolling 240	0.039	0.141	-0.326	0.046	-5.659	0.881
return_cmean	1858-02	2017-01	Rolling 60	-172.849	0.29	-28.364	0.452	-22.896	0.905
return_c_enet	1863-02	2017-01	Rolling 240	-109.129	0.122	-17.225	0.164	-33.035	0.017
sd	1858-02	2017-01	Rolling 240	-150.718	0.047	-28.942	0.229	-47.539	0.184
return_c_enet	1863-02	2017-01	Rolling 60	-452.108	0.334	-56.394	0.544	-71.241	0.907
skew	1858-02	2017-01	Rolling 60	-4.089	0.717	-28.175	0.359	-649.773	0.047
kurt	1858-02	2017-01	Rolling 60	-889.938	0.136	-802.105	0.375	-915.793	0.953
sd	1858-02	2017-01	Rolling 60	-36881.034	0.339	-4704.501	0.633	-3008.187	0.526

Panel B: Transfer Learning US OOS Tests 193102-201701

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
macro_c_enet	1931-02	2017-01	Expanding	0.103	0.035	0.023	0.037	0.029	0.001
mix_c_enet	1931-02	2017-01	Expanding	0.101	0.034	0.019	0.066	0.028	0
macro_dmspe	1926-03	2017-01	Rolling 60	-0.065	0.036	0	0.72	0.025	0.005
tbl	1926-02	2017-01	Expanding	0.105	0.029	0.02	0.143	0.025	0.033
ltr	1926-02	2017-01	Rolling 240	0.029	0.479	0.012	0.044	0.024	0.001
tms	1926-02	2017-01	Expanding	0.16	0.038	0.025	0.033	0.023	0.023
ltr	1926-02	2017-01	Expanding	0.102	0.206	0.031	0.036	0.021	0.014
infl	1926-02	2017-01	Rolling 240	0.03	0.516	0	0.497	0.021	0.03
lty	1926-02	2017-01	Expanding	0.013	0.024	0.007	0.518	0.018	0.02
macro_c_enet	1931-02	2017-01	Rolling 240	0.144	0.031	-0.011	0.115	0.017	0.015
mix_cmean	1926-02	2017-01	Expanding	-0.005	0.833	0.013	0.067	0.017	0.003
macro_cmean	1926-02	2017-01	Expanding	0.083	0.03	0.022	0.047	0.017	0.002
macro_cmean	1926-02	2017-01	Rolling 240	0.115	0.04	-0.005	0.137	0.016	0.003
dfr	1926-02	2017-01	Rolling 240	0.024	0.149	-0.015	0.929	0.014	0.008
tbl	1926-02	2017-01	Rolling 240	0.219	0.041	0.028	0.067	0.013	0.068
infl	1926-02	2017-01	Expanding	0.03	0.023	0.005	0.201	0.012	0.062
dfr	1926-02	2017-01	Expanding	0.031	0.025	0.004	0.348	0.011	0.051
mix_dmspe	1926-03	2017-01	Rolling 240	0.017	0.368	-0.006	0.798	0.011	0.116
ltr	1926-02	2017-01	Rolling 60	0.081	0.24	-0.051	0.251	0.011	0.006
tms	1926-02	2017-01	Rolling 240	0.158	0.057	0.012	0.061	0.01	0.048
dfr	1926-02	2017-01	Rolling 60	0.111	0.131	-0.057	0.927	0.01	0.027
lty	1926-02	2017-01	Rolling 240	-0.128	0.071	-0.029	0.596	0.004	0.024
macro_dmspe	1926-03	2017-01	Rolling 240	-0.137	0.034	-0.009	0.573	-0.002	0.974
dfy	1926-02	2017-01	Expanding	0.195	0.045	-0.062	0.281	-0.002	0.128
macro_dmspe	1926-03	2017-01	Expanding	-0.145	0.035	-0.014	0.434	-0.006	0.426
mix_dmspe	1926-03	2017-01	Expanding	-0.171	0.033	-0.02	0.345	-0.009	0.291
infl	1926-02	2017-01	Rolling 60	0.294	0.01	-0.124	0.034	-0.018	0.002
dy	1926-02	2017-01	Expanding	-0.004	0.706	-0.006	0.217	-0.03	0.892
mix_cmean	1926-02	2017-01	Rolling 240	0.14	0.054	-0.022	0.206	-0.048	0.038
dp	1926-02	2017-01	Expanding	0.01	0.043	0.01	0.176	-0.063	0.531
dfy	1926-02	2017-01	Rolling 240	-0.926	0.061	-0.243	0.515	-0.07	0.143
tms	1926-02	2017-01	Rolling 60	-0.319	0.803	-0.315	0.796	-0.104	0.132
macro_cmean	1926-02	2017-01	Rolling 60	-0.002	0.09	-0.175	0.207	-0.144	0.004
dp	1926-02	2017-01	Rolling 240	0.283	0.025	-0.241	0.264	-0.247	0.818
dy	1926-02	2017-01	Rolling 240	0.268	0.025	-0.446	0.263	-0.318	0.439

Predictor	Start	End	Update	Last 5 YR	P Val	Last 50 YR	P Val	All YR	P Val
lty	1926-02	2017-01	Rolling 60	-0.834	0.039	-0.56	0.562	-0.38	0.124
macro_c_enet	1931-02	2017-01	Rolling 60	-2.201	0.2	-1.932	0.132	-0.996	0.012
tbl	1926-02	2017-01	Rolling 60	-1.184	0.254	-0.449	0.974	-1.072	0.822
dfy	1926-02	2017-01	Rolling 60	-1.068	0.58	-0.494	0.529	-1.207	0.05
mix_dmspe	1926-03	2017-01	Rolling 60	-19.509	0.342	-2.658	0.562	-1.856	0.999
dp	1926-02	2017-01	Rolling 60	-2.381	0.234	-2.323	0.258	-2.915	0.045
dy	1926-02	2017-01	Rolling 60	-2.044	0.169	-3.881	0.308	-4.353	0.046
mix_cmean	1926-02	2017-01	Rolling 60	-71.887	0.278	-11.871	0.418	-9.458	0.976
mix_c_enet	1931-02	2017-01	Rolling 240	-38.255	0.046	-11.665	0.146	-30.916	0.016
mix_c_enet	1931-02	2017-01	Rolling 60	-4173.52	0.335	-506.341	0.596	-319.071	0.57

Table 6: Economic Gains: Transfer Learning

Table 6 shows the economic gains of the predictions in the transfer learning setups. The transfer learning setups fit models using the UK market and apply the models to the US market. I report economic gains calculated based on the difference between the certainty equivalent returns from the alternative predictions and the certainty equivalent return from the null prediction, i.e., the expanding means. The relative turnover is the turnover from the alternative predictions divided by the turnover of the null prediction. Panel A presents the results mainly for technical indicators and Panel B presents the economic gains mainly for macroeconomic predictors. The CER gains are annualized.

Panel A: Transfer Learning US Economic Gains 185802-201701

Predictor	Start	End	Update	CER Gains	Relative Turnover
lag1	1858-02	2017-01	Rolling 240	3.473	39.685
lag1	1858-02	2017-01	Expanding	3.088	49.709
lag1	1858-02	2017-01	Rolling 60	2.473	33.546
ma_2_12	1858-02	2017-01	Expanding	2.399	7.43
ma_2_12	1858-02	2017-01	Rolling 240	2.165	7.711
mean12	1858-02	2017-01	Rolling 240	2.045	9.175
ma_2_9	1858-02	2017-01	Expanding	2.043	9.755
return_dmspe	1858-03	2017-01	Rolling 240	1.925	4.006
mean9	1858-02	2017-01	Rolling 240	1.878	10.687
mean12	1858-02	2017-01	Expanding	1.804	5.648
ma_2_9	1858-02	2017-01	Rolling 240	1.717	9.381
return_cmean	1858-02	2017-01	Expanding	1.657	13.698
mean9	1858-02	2017-01	Expanding	1.611	6.068
mom9	1858-02	2017-01	Rolling 240	1.609	7.147
mom9	1858-02	2017-01	Expanding	1.477	5.437
mom12	1858-02	2017-01	Rolling 240	1.459	5.772
ma_1_12	1858-02	2017-01	Expanding	1.444	30.779
ma_1_12	1858-02	2017-01	Rolling 240	1.331	28.558
mom12	1858-02	2017-01	Expanding	1.2	3.686
ma_1_9	1858-02	2017-01	Rolling 240	1.167	24.223
ma_1_9	1858-02	2017-01	Expanding	1.128	28.928
return_c_enet	1863-02	2017-01	Expanding	0.96	13.227
mean9	1858-02	2017-01	Rolling 60	0.715	10.702
ma_2_12	1858-02	2017-01	Rolling 60	0.689	10.435
ma_2_9	1858-02	2017-01	Rolling 60	0.652	10.369
mean12	1858-02	2017-01	Rolling 60	0.534	11.176
lag3	1858-02	2017-01	Expanding	0.391	16.518

Predictor	Start	End	Update	CER Gains	Relative Turnover
skew	1858-02	2017-01	Expanding	0.32	0.924
ma_3_9	1858-02	2017-01	Rolling 240	0.3	14.413
return_cmean	1858-02	2017-01	Rolling 240	0.295	7.958
mom12	1858-02	2017-01	Rolling 60	0.275	8.309
mom9	1858-02	2017-01	Rolling 60	0.248	9.267
ma_3_9	1858-02	2017-01	Expanding	0.244	14.505
ma_3_12	1858-02	2017-01	Expanding	0.218	13.556
lag2	1858-02	2017-01	Expanding	0.124	27.321
kurt	1858-02	2017-01	Expanding	0.056	1.103
ma_3_12	1858-02	2017-01	Rolling 240	0.04	11.6
ma_1_12	1858-02	2017-01	Rolling 60	-0.036	24.128
ma_3_12	1858-02	2017-01	Rolling 60	-0.164	14.656
kurt	1858-02	2017-01	Rolling 240	-0.391	6.54
ma_1_9	1858-02	2017-01	Rolling 60	-0.399	23.618
ma_3_9	1858-02	2017-01	Rolling 60	-0.477	15.172
sd	1858-02	2017-01	Expanding	-0.794	0.347
return_dmspe	1858-03	2017-01	Rolling 60	-0.893	11.197
lag2	1858-02	2017-01	Rolling 240	-0.908	25.251
lag2	1858-02	2017-01	Rolling 60	-1.023	29.233
return_dmspe	1858-03	2017-01	Expanding	-1.175	0.781
lag3	1858-02	2017-01	Rolling 60	-1.36	25.608
kurt	1858-02	2017-01	Rolling 60	-1.607	10.023
return_c_enet	1863-02	2017-01	Rolling 240	-1.804	5.317
lag3	1858-02	2017-01	Rolling 240	-1.87	23.684
return_cmean	1858-02	2017-01	Rolling 60	-2.587	9.857
sd	1858-02	2017-01	Rolling 240	-2.595	4.699
sd	1858-02	2017-01	Rolling 60	-3.178	7.829
skew	1858-02	2017-01	Rolling 240	-3.182	4.357
return_c_enet	1863-02	2017-01	Rolling 60	-3.832	9.299
skew	1858-02	2017-01	Rolling 60	-4.496	8.918

Panel B: Transfer Learning US Economic Gains 192602-201701

Predictor	Start	End	Update	CER Gains	Relative Turnover
macro_cmean	1926-02	2017-01	Rolling 60	3.38	5.724
infl	1926-02	2017-01	Rolling 60	3.226	7.616
ltr	1926-02	2017-01	Rolling 240	2.631	21.809
tbl	1926-02	2017-01	Rolling 240	2.498	5.335
tbl	1926-02	2017-01	Rolling 60	2.419	8.435
dfy	1926-02	2017-01	Rolling 240	2.394	7.812
tms	1926-02	2017-01	Expanding	2.394	4.705
macro_c_enet	1931-02	2017-01	Rolling 240	2.284	4.067
tbl	1926-02	2017-01	Expanding	2.278	2.546
mix_cmean	1926-02	2017-01	Rolling 240	2.159	8.241
infl	1926-02	2017-01	Rolling 240	2.142	4.106
lty	1926-02	2017-01	Rolling 240	2.099	4.314
ltr	1926-02	2017-01	Rolling 60	2.091	18.753
macro_cmean	1926-02	2017-01	Rolling 240	2.071	3.566
macro_c_enet	1931-02	2017-01	Expanding	2.001	6.796
mix_c_enet	1931-02	2017-01	Expanding	1.98	12.357
ltr	1926-02	2017-01	Expanding	1.854	27.251
lty	1926-02	2017-01	Expanding	1.814	2.319
dy	1926-02	2017-01	Rolling 60	1.724	4.142
macro_cmean	1926-02	2017-01	Expanding	1.689	5.494
dfr	1926-02	2017-01	Rolling 240	1.679	6.257
dfr	1926-02	2017-01	Rolling 60	1.587	8.514
mix_cmean	1926-02	2017-01	Expanding	1.555	10.312
tms	1926-02	2017-01	Rolling 240	1.555	4.936
dfy	1926-02	2017-01	Expanding	1.502	4.942
macro_dmspe	1926-03	2017-01	Rolling 60	1.469	4.084
tms	1926-02	2017-01	Rolling 60	1.298	8.711
infl	1926-02	2017-01	Expanding	1.241	1.547
dfr	1926-02	2017-01	Expanding	1.103	1.79
dp	1926-02	2017-01	Rolling 60	1.045	5.843
mix_dmspe	1926-03	2017-01	Rolling 240	0.962	2.964
dp	1926-02	2017-01	Rolling 240	0.793	1.893
dy	1926-02	2017-01	Expanding	0.715	2.382
dp	1926-02	2017-01	Expanding	0.106	1.891
macro_c_enet	1931-02	2017-01	Rolling 60	0.104	3.448

Predictor	Start	End	Update	CER Gains	Relative Turnover
dy	1926-02	2017-01	Rolling 240	0.102	1.738
dfy	1926-02	2017-01	Rolling 60	-0.089	9.599
macro_dmspe	1926-03	2017-01	Rolling 240	-0.257	1.136
mix_dmspe	1926-03	2017-01	Rolling 60	-0.603	10.698
macro_dmspe	1926-03	2017-01	Expanding	-0.853	0.67
lty	1926-02	2017-01	Rolling 60	-1.084	9.886
mix_dmspe	1926-03	2017-01	Expanding	-1.214	0.428
mix_cmean	1926-02	2017-01	Rolling 60	-1.728	12.908
mix_c_enet	1931-02	2017-01	Rolling 240	-1.757	4.833
mix_c_enet	1931-02	2017-01	Rolling 60	-3.84	9.903

Table 7: Stability of Out-of-Sample Predictability

Table 7 shows the stability of out-of-sample (OOS) predictability. I calculate the 5-year rolling window OOS R^2 and take the standard deviation to form the measure. Panel A and B reports the standard deviations for technical indicators and macroeconomic predictors respectively. The update frequency, i.e., “Expand”, “Roll60” and “Roll240” indicates the update window for prediction models. The expanding window, “Expand”, uses all past observations. “Roll60” indicates 60-month rolling window update using the past 60 months and “Roll240” indicates 240-month rolling window update using the past 240 months. All numbers are annualized.

Panel A: OOS Predictability Stability of Technical Indicators

	UK			US			Transfer		
Predictor	Expand	Roll60	Roll240	Expand	Roll60	Roll240	Expand	Roll60	Roll240
kurt	0.232	0.429	0.179	0.116	0.332	0.199	0.047	2547.175	28.405
lag1	0.325	0.318	0.278	0.244	0.25	0.201	0.263	0.231	0.184
lag2	0.116	0.245	0.139	0.023	0.189	0.112	0.082	0.178	0.093
lag3	0.105	0.261	0.14	0.068	0.205	0.109	0.055	0.172	0.123
ma_1_12	0.169	0.413	0.188	0.123	0.186	0.122	0.085	0.159	0.102
ma_1_9	0.112	0.242	0.169	0.118	0.18	0.11	0.085	0.161	0.104
ma_2_12	0.103	0.2	0.158	0.136	0.21	0.139	0.079	0.197	0.111
ma_2_9	0.121	0.223	0.172	0.12	0.203	0.139	0.078	0.194	0.112
ma_3_12	0.185	0.353	0.147	0.077	0.211	0.118	0.067	0.197	0.097
ma_3_9	0.156	0.366	0.132	0.063	0.197	0.111	0.069	0.247	0.105
mean12	0.115	0.268	0.17	0.108	0.211	0.13	0.069	0.232	0.161
mean9	0.113	0.272	0.176	0.105	0.216	0.127	0.062	0.255	0.136
mom12	0.082	0.221	0.194	0.127	0.199	0.15	0.069	0.205	0.111
mom9	0.106	0.231	0.182	0.099	0.216	0.148	0.075	0.276	0.111
return_c_enet	0.057	0.15	0.121	0.082	0.161	0.105	0.032	70.696	90.622
return_cmean	0.07	0.196	0.143	0.066	0.159	0.11	0.068	35.19	0.371
return_dmspe	0.037	0.033	0.033	0.052	0.046	0.051	0.048	7.776	0.118
sd	0.315	0.407	0.192	0.085	0.303	0.187	0.097	4744.884	74.453
skew	0.137	0.315	0.157	0.053	0.233	0.149	0.055	2674.022	15.731

Panel B: OOS Predictability Stability of Macroeconomic Predictors

	UK			US			Transfer		
Predictor	Expand	Roll60	Roll240	Expand	Roll60	Roll240	Expand	Roll60	Roll240
dfr	0.114	0.176	0.122	0.098	0.248	0.164	0.03	0.155	0.094
dfy	0.144	0.224	0.164	0.129	0.276	0.155	0.15	1.148	0.304
dp	0.11	0.201	0.133	0.106	0.246	0.143	0.19	4.435	0.475
dy	0.109	0.218	0.131	0.098	0.34	0.148	0.115	8.409	0.595
infl	0.102	0.227	0.161	0.105	0.263	0.172	0.028	0.342	0.094
ltr	0.143	0.178	0.16	0.104	0.265	0.122	0.049	0.179	0.089
lty	0.139	0.246	0.192	0.139	0.221	0.166	0.053	0.698	0.145
macro_c_enet	0.109	0.164	0.116	0.089	0.238	0.095	0.052	1.79	0.143
macro_cmean	0.109	0.161	0.115	0.088	0.202	0.102	0.034	0.514	0.113
macro_dmspe	0.025	0.031	0.026	0.042	0.045	0.046	0.041	0.047	0.035
tbl	0.151	0.544	0.186	0.111	0.281	0.196	0.075	5.955	0.099
tms	0.141	0.295	0.17	0.113	0.253	0.126	0.068	0.398	0.099

Table 8: Out-of-Sample R^2, GDP and Extreme Equity Premiums

Table 8 shows the annual out-of-sample (OOS) R^2 conditional on the economic rare events for the UK. Panel A investigates the rare GDP levels. Panel B focuses on the extreme equity premiums. Panel C interacts the GDP events with the equity premium events. The column "Non Event YR" shows the OOS R^2s for the non-event years and the column "Event YR" shows the OOS R^2s for the event years. All OOS R^2s are annualized.

Panel A: Predictability and GDP

Event	Non Event YR	Event YR
Decreasing GDP	0.011	-0.001
$<$5 Percentile GDP	0.004	0.027
$>$95 Precentile GDP	0.01	-0.003
GDP Turning Point	0.004	0.023
GDP Turning Negative	0.008	0.016
GDP Turning Positive	0.003	0.032
Before GDP Turning Point	0.017	-0.016
Before GDP Turning Negative	0.009	0.002
Before GDP Turning Positive	0.014	-0.024

Panel B: Predictability and Extreme Equity Premiums

Event	Non Event YR	Event YR
Extreme Equity Premium	0.013	0.005
Positive Extreme Equity Premium	-0.022	0.064
Negative Extreme Equity Premium	0.042	-0.041

Panel C: Predictability and the Interaction between GDP and Extreme Equity Premiums

Event	Non Event YR	Event YR
GDP Turning Point X Extreme Equity Premium	0.001	0.03
GDP Turning Positive X Extreme Equity Premium	0.007	0.009
GDP Turning Negative X Extreme Equity Premium	0.002	0.049
GDP Turning Point X Positive Extreme Equity Premium	-0.002	0.104
GDP Turning Positive X Positive Extreme Equity Premium	-0.002	0.137
GDP Turning Negative X Positive Extreme Equity Premium	0.008	0.007
GDP Turning Point X Negative Extreme Equity Premium	0.011	-0.008
GDP Turning Positive X Negative Extreme Equity Premium	0.016	-0.135
GDP Turning Negative X Negative Extreme Equity Premium	0.001	0.066

Table 9: Predictability and Rare Events

Table 9 presents the relation between the out-of-sample predictability in the UK and non-economic rare events in the UK history, including famine, epidemics, pandemics and major wars. Overall, the non-economic rare events have a categorical variable correlation of 0.07 (Cramer's V) with the decreasing GDP periods. 34% of all years have decreasing GDP. Among the rare event years, 50% famine years have decreasing GDP. 36% epidemic and pandemic years have decreasing GDP. 38% years during major wars have decreasing GDP. The predictability concentration over the non-economic rare event years is measured by the annualized out-of-sample (OOS) R^2.

Event	Non Event YR	Event YR
Famine	0.008	0.067
Disease	0.005	0.075
Major War	0.006	0.017
Population Decrease	0.01	-0.001
<5 Percentile Population Change	0.009	0.003
All Rare Events	0.008	0.004