Exchange Rate Prediction with Machine Learning and a Smart Carry Trade Portfolio

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Abstract

We establish the out-of-sample predictability of monthly exchange rates via machine learning techniques based on 70 predictors capturing country characteristics, global variables, and their interactions. To better guard against overfitting in our high-dimensional and noisy data environment, we make additional adjustments to "off-the-shelf" implementations of machine learning techniques, including imposing economic constraints. The resulting forecasts consistently outperform the no-change benchmark, which has proven difficult to beat. Country characteristics are important for forecasting, once they interact with global variables. Machine learning forecasts also markedly improve the performance of a carry trade portfolio, especially since the global financial crisis.

JEL classifications: C45, F31, F37, G11, G12, G15

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1. Introduction

The specter of Meese and Rogoff (1983) continues to haunt international finance: despite an array of theoretical models linking fundamentals to exchange rates, it is difficult to outperform the no-change benchmark forecast of the exchange rate on an out-of-sample basis, especially at short horizons. Of course, it is not surprising that it is difficult to do so, as developed-country currencies are traded in quite liquid and institutional investor-dominated markets. Thus, we expect that exchange rate fluctuations will contain only a small predictable component. However, the same is true for equities, and while we also expect a small predictable component in equity returns, the apparent consensus is that short-horizon, out-of-sample stock return predictability exists to a statistically and economically significant degree (e.g., Rapach and Zhou 2013). In contrast, the empirical evidence for short-horizon, out-of-sample exchange rate predictability appears considerably weaker and more precarious (e.g., Kilian and Taylor 2003; Rossi 2013), so that such a consensus does not prevail with respect to exchange rates.

In this paper, we find that, like equity returns, exchange rates are predictable on an out-of-sample basis, once we employ appropriate methods. Specifically, we use a rich information set and machine learning techniques to improve monthly out-of-sample forecasts of US dollar exchange rates for a group of developed countries.[1] The information set is comprised of ten country characteristics and six global variables. The country characteristics include various macroeconomic and financial variables, such as inflation, interest rate, unemployment gap, and valuation ratio differentials, which can be motivated by purchasing power parity (PPP), uncovered interest parity (UIP), the Taylor (1993) rule, and uncovered equity parity (UEP), among other theories. The global variables include economic and monetary policy uncertainty indices (Baker, Bloom, and Davis 2016), a geopolitical risk index (Caldara and

[1]Machine learning is becoming popular in finance for predicting equity returns with large information sets (e.g., Rapach, Strauss, and Zhou 2013; Chinco, Clark-Joseph, and Ye 2019; Chen, Pelger, and Zhu 2020; Freyberger, Neuhierl, and Weber 2020; Gu, Kelly, and Xiu 2020; Han et al. 2021; Dong et al. forthcoming).

Iacoviello 2018), as well as measures of global foreign exchange (FX) volatility, illiquidity, and correlation (Menkhoff et al. 2012a; Mueller, Stathopoulos, and Vedolin 2017). In order to allow for the predictive relationships between the country characteristics and exchange rate changes to vary with global conditions, we interact the country characteristics with the global variables, producing a set of 70 predictors. Previous studies typically focus on a limited number of country characteristics and do not consider interactions with global variables, which we find to be important. The 70 predictors serve as explanatory variables in a panel predictive regression framework.

We begin with a linear panel specification for generating out-of-sample forecasts. Given our high-dimensional setting with 70 predictors, it is vital to guard against *overfitting* when estimating the panel predictive regressions. Because monthly exchange rate changes contain an intrinsically large unpredictable component, we need to contend with very noisy data, creating an even more urgent need to alleviate overfitting. To do so, we estimate the panel predictive regressions via the *elastic net* (ENet, Zou and Hastie 2005), a refinement of the popular *least absolute shrinkage and selection operator* (LASSO, Tibshirani 1996) from machine learning. By construction, conventional ordinary least squares (OLS) estimation maximizes the fit of the model over the estimation (or training) sample, which can lead to overfitting the model to the training sample and thus poor out-of-sample performance. The ENet is a *penalized regression* technique that shrinks the estimated coefficients towards zero, thereby mitigating overfitting. The penalty term in the ENet includes both an ℓ_1 component—as in the LASSO—and an ℓ_2 component—as in ridge regression (Hoerl and Kennard 1970); the former permits shrinkage to zero, so that the ENet also performs variable selection. Instead of conventional cross validation, we use the extended regularization information criterion (ERIC, Hui, Warton, and Foster 2015), which is a modification of the Bayesian information criterion (BIC, Schwarz 1978), to select (or tune) the ENet's shrinkage hyperparameter (λ). ERIC is a more stringent method for tuning λ, in the sense that it tends to select a larger value for λ and thus induce more shrinkage, thereby better guarding against overfitting in our high-dimensional and noisy data environment.

We further guard against overfitting by imposing economic constraints. After standardizing the predictors, we set the intercept terms in the panel predictive regressions to zero, thereby imposing the economic restrictions that the average exchange rate changes are zero. These restrictions are consistent with the data and help to guard against overfitting by reducing the parameter space.[2] We also pool the data in our panel framework, which imposes slope homogeneity restrictions across countries to further reduce the parameter space. Reducing the number of parameters we need to estimate helps to improve out-of-sample performance in light of the bias-variance tradeoff. We refer to the forecasts based on OLS and ENet estimation of the linear panel predictive regressions as the Linear-OLS and Linear-ENet forecasts, respectively.

In order to permit nonlinearities when predicting exchange rates, we also generate forecasts based on *deep neural networks* (DNNs). DNNs are popular machine learning models that allow for complex nonlinear predictive relationships via a network architecture with multiple hidden layers containing neurons activated by predictive signals. In order to approximate general predictive relationships, DNNs are highly parameterized, which can make them susceptible to overfitting, especially in our noisy data environment.[3] To better guard against overfitting, we move beyond an "off-the-shelf" implementation of deep learning. Specifically, we set the intercept terms for the weights to zero. These economic restrictions, which are analogous to setting the intercept terms in the linear panel predictive regressions to zero, again help to guard against overfitting by reducing the number of weights we need to estimate. In addition, we include ℓ_1 and ℓ_2 penalty components in the objective function and employ dropout (Hinton et al. 2012; Srivastava et al. 2014) when training the DNNs.

[2] Kozak, Nagel, and Santosh (2020) impose economically motivated priors in the context of estimating stochastic discount factor coefficients via the LASSO using equity return data. Nagel (2021) emphasizes the importance of combining economic insights with machine learning tools for empirical asset pricing.

[3] The parameters in a DNN are typically referred to as *weights*.

We also consider an *ensemble* forecast that takes the average of the Linear-ENet and DNN forecasts. The ensemble forecast recognizes that it is difficult to know a priori the best individual forecast, and it allows us to take advantage of potential complementarities in the Linear-ENet and DNN forecasts.

Mimicking the situation of a forecaster in real time, we generate monthly out-of-sample forecasts based on the 70 predictors by recursively estimating the linear panel predictive regression and DNN models each month. Based on data availability (and after allowing for a ten-year initial training sample), the out-of-sample period spans 1995:01 to 2020:09. We compute forecasts for the entire out-of-sample period for the United Kingdom, Switzerland, Japan, Canada, Australia, New Zealand, Sweden, Norway, and Denmark; for the Euro area, the out-of-sample period begins in 2000:02. We refer to the exchange rates for these ten countries as the G10.[4] For Germany, Italy, France, and the Netherlands, the out-of-sample period ends in 1998:12, corresponding to their adoption of the Euro.

We find that the information in the rich set of predictors is useful for outperforming the stringent no-change benchmark forecast over the 1995:01 to 2020:09 out-of-sample period, provided we guard against overfitting. As expected, the Linear-OLS forecasts substantially underperform the no-change benchmark in terms of mean squared prediction error (MSPE) for all of the countries, a clear manifestation of overfitting. In contrast, the Linear-ENet, DNN, and ensemble forecasts outperform the no-change benchmark for twelve, 13, and all 14 of the countries, respectively. Based on the Campbell and Thompson (2008) out-of-sample R^2 (R^2_{OS}) statistic, which measures the proportional decrease in MSPE for a competing forecast vis-à-vis a benchmark, the improvements in forecast accuracy are quantitatively large in the context of the extensive literature surveyed by Rossi (2013). The improvements in MSPE vis-à-vis the no-change benchmark are also statistically significant in many cases

[4]The G11 currencies are the US dollar, Euro, British pound, Swiss franc, Japanese yen, Canadian dollar, Australian dollar, New Zealand dollar, Swedish krona, Norwegian krone, and Danish krone. With the US dollar serving as the base currency, we label our set of ten exchange rates the G10.

according to the Clark and West (2007) test. The ensemble forecasts deliver the best overall performance: the R^2_{OS} statistics are positive for all of the countries, are above 1% (2%) for ten (six) countries, and reach as high as 3.12% (for the United Kingdom). The R^2_{OS} statistic is also a sizable 1.88% (significant at the 1% level) for the entire group of countries taken together.

Based on the graphical device of Goyal and Welch (2003, 2008), the machine learning forecasts outperform the no-change benchmark on a reasonably consistent basis over time. The outperformance is particularly strong during the worst phase of the global financial crisis in late 2008. Overall, by utilizing a rich information set—while adequately guarding against overfitting—our machine learning approach makes considerable progress in solving the Meese and Rogoff (1983) no-predictability puzzle, providing among the best short-horizon exchange rate forecasts available to date.

In order to glean insight into the relevance of the individual predictors in the models underlying the forecasts, we assess variable importance using the recently developed approach of Greenwell, Boehmke, and McCarthy (2018), which is based on partial dependence plots (PDPs, Friedman 2001). PDPs are useful in their own right for exploring the strength of nonlinearities in fitted models. We find that popular predictors from the literature, such as inflation and government bill yield differentials, are important in the fitted Linear-ENet and DNN models when they interact with global FX volatility. In essence, the predictive relationships between the inflation and bill yield differentials and expected US dollar appreciation accord more closely to the logic of PPP and UIP, respectively, as global FX volatility increases. The unemployment gap differential and its interactions with a number of global variables are also important, especially for the DNN. PDPs for the DNN indicate that nonlinearities are primarily important for more extreme positive or negative values of the predictors.

We also explore the economic implications of out-of-sample exchange rate predictability for carry trade investment strategies. The popular carry trade entails going long (short) currencies with relatively high (low) interest rates. For a US investor who goes long (short) the currency for country i (US dollar), based on covered interest parity, we can approximate the log excess return for the investment as

$$rx_{i,t+1} \approx (r_{i,t} - r_{\mathrm{US},t}) - \Delta s_{i,t+1}, \tag{1}$$

where $rx_{i,t}$ is the month-t log currency excess return for country i, $r_{i,t}$ ($r_{\mathrm{US},t}$) is the government bill yield for country i (the United States), $s_{i,t} = \log(S_{i,t})$, and $S_{i,t}$ is the spot exchange rate expressed as the number of country-i currency units per US dollar. Beginning with Hansen and Hodrick (1980), Bilson (1981), and Fama (1984), a voluminous literature finds that UIP does not hold and that the conditional expectation of $rx_{i,t+1}$ is positive in Equation (1) when $r_{i,t} - r_{\mathrm{US},t} > 0$.[5] Compared to a variety of investment strategies, conventional carry trade portfolios deliver impressive Sharpe ratios prior to the global financial crisis (e.g., Burnside, Eichenbaum, and Rebelo 2011; Lustig, Roussanov, and Verdelhan 2011).[6] However, they suffered large losses in late 2008, and their performance has since deteriorated in the wake of the global financial crisis (e.g., Melvin and Taylor 2009; Jordà and Taylor 2012; Daniel, Hodrick, and Lu 2017; Melvin and Shand 2017).[7]

From the perspective of Equation (1), if an investor's forecast of $\Delta s_{i,t+1}$ is zero—in the spirit of Meese and Rogoff (1983)—then the investor's forecast of $rx_{i,t+1}$ is simply the bill yield differential ($r_{i,t} - r_{\mathrm{US},t}$)—in the spirit of the usual carry trade. In this vein, we construct an optimal portfolio for a mean-variance investor who allocates across available foreign currencies by relying on bill yield differentials to forecast foreign currency excess returns. We label this a *Basic Optimal* (Basic-Opt) carry trade portfolio, as the investor

[5]See Froot and Thaler (1990), Taylor (1995), and Burnside (2018) for surveys of UIP.

[6]Studies that explore risk-based explanations for carry trade returns include Burnside et al. (2011), Lustig, Roussanov, and Verdelhan (2011), Menkhoff et al. (2012a), Dobrynskaya (2014), Jurek (2014), Lettau, Maggiori, and Weber (2014), and Dahlquist and Hasseltoft (2020).

[7]Brunnermeier, Nagel, and Pedersen (2009) provide an explanation for carry trade crashes based on funding-constrained speculators.

ignores exchange rate predictability when forecasting excess returns. The Basic-Opt portfolio delivers impressive performance before the global financial crisis. However, it suffers large losses in late 2008, and its cumulative return is essentially flat thereafter.[8]

We also construct a *Smart Optimal* (Smart-Opt) carry trade portfolio, in which the mean-variance investor augments the bill yield differential with the ensemble forecast of $\Delta s_{i,t+1}$ to forecast the currency excess return, thereby attempting to exploit exchange rate predictability when allocating across currencies.[9] The Smart-Opt portfolio provides substantial economic value to the investor vis-à-vis the Basic-Opt portfolio, generating an annualized increase in certainty equivalent return of 340 basis points. The superior performance of the Smart-Opt portfolio is evident both before and after the global financial crisis, although it is especially apparent starting in late 2008. The Smart-Opt portfolio experiences a smaller loss than the Basic-Opt portfolio in September of 2008, generates much larger gains in the last three months of 2008, and performs well subsequently. Consistent with the US dollar's safe-haven role during the crisis, the ensemble forecasts predict substantial depreciations for many foreign currencies in late 2008, which lead to markedly different allocations for the Smart-Opt vis-à-vis the Basic-Opt portfolio. The Smart-Opt portfolio also generates substantial alpha both before and after the crisis in the context of the Lustig, Roussanov, and Verdelhan (2011) currency factor model.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 discusses the specification and estimation of the models used to generate the out-of-sample

[8]Daniel, Hodrick, and Lu (2017) also construct an optimal carry trade portfolio for a mean-variance investor who uses interest rate differentials to forecast currency excess returns. Our Basic-Opt portfolio performs similarly to theirs. A conventional carry trade portfolio that sorts currencies based on bill yield differentials and goes long (short) the fifth (first) quintile performs even worse than the Basic-Opt portfolio.

[9]The results are similar when the investor uses the Linear-ENet or DNN forecast (as reported in Section 5). Della Corte, Sarno, and Tsiakas (2009) construct mean-variance optimal portfolios for a US investor who allocates across US, British, German, and Japanese short-term bonds using a handful of fundamentals to forecast exchange rates. Jordà and Taylor (2012) use a small number of fundamentals to improve carry trade strategies (but not in a mean-variance optimal framework). Della Corte, Jeanneret, and Patelli (2020) consider a mean-variance investor who allocates between US short-term bonds and a Euro-denominated cash account using a credit-implied risk premium to forecast the exchange rate.

exchange rate forecasts. Section 4 analyzes forecast accuracy and predictor importance. Section 5 discusses the construction of the Basic-Opt and Smart-Opt carry trade portfolios and analyzes their performance. Section 6 concludes.

2. Data

This section describes the data used in our analysis. Section A1 of the Internet Appendix provides further details on the data sources and construction of the variables.

2.1. Exchange Rates

We begin with daily exchange rate data from Barclays and Reuters via Datastream. We convert daily spot exchange rates to a monthly frequency using end-of-month values (e.g., Burnside et al. 2011; Lustig, Roussanov, and Verdelhan 2011). Our sample consists of the following 14 countries: the United Kingdom, Switzerland, Japan, Canada, Australia, New Zealand, Sweden, Norway, Denmark, the Euro area, Germany, Italy, France, and the Netherlands.[10] Germany, Italy, France, and the Netherlands are replaced by the Euro area after the Euro's introduction in 1999. We refer to the group of ten countries excluding Germany, Italy, France, and the Netherlands as the G10.

As in Section 1, we use $S_{i,t}$ to denote the month-t spot exchange rate, expressed as the number of country-i currency units per US dollar (e.g., Lustig, Roussanov, and Verdelhan 2011; Menkhoff et al. 2012a,b). An increase in $S_{i,t}$ thus represents an appreciation of the US dollar. The country-i log exchange rate change is denoted by $\Delta s_{i,t}$, where $s_{i,t} = \log(S_{i,t})$. Table 1 reports summary statistics for the 14 exchange rates. The second column reports the sample period for each country. With the exceptions of four countries, the sample ends

[10] Our universe of exchange rates is similar to the sample of developed countries employed in other studies (e.g., Lustig, Roussanov, and Verdelhan 2011; Menkhoff et al. 2012a), with the exception of Belgium, which we exclude due to a lack of data availability for the country characteristics in Section 2.2.

in 2020:09; for France, Germany, Italy, and the Netherlands, the sample ends in 1998:12, the last month for which these countries had their own currencies. Based on data availability for the predictors, the sample begins in 1985:01 for all of the countries, with the exception of the Euro area, where the sample begins in 1999:02, corresponding to the introduction of the Euro in January of 1999.

Table 1: Summary Statistics

The table reports summary statistics for monthly log exchange rate changes measured against the US dollar. The country-i log exchange rate change is $\Delta s_{i,t}$, where $s_{i,t} = \log(S_{i,t})$ and $S_{i,t}$ is the month-t spot exchange rate for country i (number of country-i currency units per US dollar). The annualized mean (volatility) in the third (fourth) column is the monthly mean (standard deviation) multiplied by 12 $\left(\sqrt{12}\right)$.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Country	Sample Period	Ann. Mean	Ann. Vol.	Skewness	Excess Kurtosis	Autocorr.
United Kingdom	1985:01–2020:09	−0.30%	9.98%	0.30	2.52	0.06
Switzerland	1985:01–2020:09	−2.90%	11.14%	−0.04	0.96	−0.01
Japan	1985:01–2020:09	−2.43%	10.88%	−0.35	1.82	0.04
Canada	1985:01–2020:09	0.02%	7.34%	0.48	3.99	−0.04
Australia	1985:01–2020:09	0.39%	11.64%	0.67	2.36	0.04
New Zealand	1985:01–2020:09	−0.92%	12.04%	0.39	1.83	−0.03
Sweden	1985:01–2020:09	−0.01%	10.98%	0.44	1.50	0.10
Norway	1985:01–2020:09	0.08%	11.03%	0.43	1.11	0.02
Denmark	1985:01–2020:09	−1.61%	10.27%	0.19	0.79	0.03
Euro area	1999:02–2020:09	−0.14%	9.55%	0.16	1.13	0.03
Germany	1985:01–1998:12	−4.55%	11.61%	0.32	0.32	0.03
Italy	1985:01–1998:12	−1.13%	11.39%	0.79	2.03	0.09
France	1985:01–1998:12	−3.89%	11.13%	0.42	0.54	0.01
Netherlands	1985:01–1998:12	−4.56%	11.57%	0.28	0.34	0.03

The annualized means in the third column of Table 1 are generally small in magnitude. In fact, none of the means are significant at conventional levels. The annualized volatilities in the fourth column are typically sizable; apart from Canada (7.34%), they range from 9.55% (Euro area) to 12.04% (New Zealand). With the exceptions of Switzerland and Japan, the exchange rate changes are positively skewed (fifth column), while all of the exchange rate changes exhibit excess kurtosis (sixth column). The autocorrelations in the last column are all relatively small in magnitude. Overall, the summary statistics in Table 1 reflect well-known empirical features of exchange rates.

2.2. Country Characteristics

We consider ten monthly country characteristics computed using macroeconomic and financial data from Global Financial Data and the Organization for Economic Cooperation and Development:

Inflation differential ($\mathrm{INF}_{i,t}$). Difference in consumer price index inflation rates for country i and the United States.

Unemployment gap differential ($\mathrm{UN}_{i,t}$). Difference in unemployment gaps for country i and the United States. The unemployment gap is the cyclical component of the unemployment rate computed using the Christiano and Fitzgerald (2003) band-pass filter for periodicities between six and 96 months.[11]

Bill yield differential ($\mathrm{BILL}_{i,t}$). Difference in three-month government bill yields for country i and the United States.

Note yield differential ($\mathrm{NOTE}_{i,t}$). Difference in five-year government note yields for country i and the United States.

[11] We compute the unemployment gap only using data available at the time of forecast formation. The Hodrick and Prescott (1997) filter is often used to compute output and unemployment gaps. Because we are interested in out-of-sample forecasting, we use the Christiano and Fitzgerald (2003) band-pass filter, as it performs better at the right-hand endpoint.

Bond yield differential ($\text{BOND}_{i,t}$). Difference in ten-year government bond yields for country i and the United States.

Dividend yield differential ($\text{DP}_{i,t}$). Difference in dividend yields for country i and the United States.

Price-earnings differential ($\text{PE}_{i,t}$). Difference in price-earnings ratios for country i and the United States.

Stock market time-series momentum differential ($\text{SRET12}_{i,t}$). Difference in cumulative twelve-month stock market returns for country i and the United States.

Idiosyncratic volatility ($\text{IV}_{i,t}$). Integrated volatility computed using the fitted residuals for the Lustig, Roussanov, and Verdelhan (2011) two-factor model estimated using daily data for month t for country-i log currency excess returns.

Idiosyncratic skewness ($\text{IS}_{i,t}$). Integrated skewness computed using the fitted residuals for the Lustig, Roussanov, and Verdelhan (2011) two-factor model estimated using daily data for month t for country-i log currency excess returns.

The country characteristics include a variety of macroeconomic and financial measures, all of which are based on data readily available to FX market participants.[12] The inflation differential relates to PPP, while the inflation and unemployment gap differentials constitute Taylor (1993) rule fundamentals (e.g., Engel and West 2005; Molodtsova and Papell 2009), which appear to perform better for exchange rate prediction than fundamentals based on the traditional monetary model (Frenkel 1976; Mussa 1976). The bill yield differential relates to the voluminous UIP literature, while longer-term yield differentials are considered by Ang and Chen (2011) and Chen and Tsang (2013) in the context of yield curves. Hau and Rey (2006) and Cenedese et al. (2016), among others, employ valuation ratio differentials to

[12] We account for the publication lag in the consumer price index and unemployment rate, so that $\text{INF}_{i,t}$ and $\text{UN}_{i,t}$ correspond to data for month $t-1$ that are reported in month t.

analyze UEP. The other country characteristics represent additional financial measures that are potentially relevant to market participants.

2.3. Global Variables

We consider six global variables:

Economic policy uncertainty (EPU_t). Baker, Bloom, and Davis (2016) economic policy uncertainty index based on coverage frequencies in ten major US newspapers.

Monetary policy uncertainty (MPU_t). Baker, Bloom, and Davis (2016) monetary policy uncertainty index based on coverage frequencies in ten major US newspapers.

Geopolitical risk (GR_t). Caldara and Iacoviello (2018) geopolitical risk index based on newspaper coverage.

Global FX volatility (GVOL_t). Following Menkhoff et al. (2012a), global FX volatility is the average for the month of the daily cross-sectional averages of the absolute values of log exchange rate changes.

Global FX illiquidity (GILL_t). Following Menkhoff et al. (2012a), global FX illiquidity is the average for the month of the daily cross-sectional averages of the bid-ask spreads for the currencies.

Global FX correlation (GCOR_t). Similarly to Mueller, Stathopoulos, and Vedolin (2017), we measure global FX correlation as the average of the realized correlations for all currency pairs computed using daily log currency excess returns for the month.

The global variables capture general economic conditions that potentially affect the predictive ability of the country characteristics.[13]

[13] We follow Menkhoff et al. (2012a) and Mueller, Stathopoulos, and Vedolin (2017) by measuring GVOL_t, GILL_t, and GCOR_t as the residuals from fitted first-order autoregressive processes. We only use data avail-

3. Panel Predictive Regressions

In this section, we specify the linear panel predictive regression and DNN models used to construct the out-of-sample forecasts.

3.1. Linear Specification

We collect the month-t characteristics for country i and month-t global variables in the following vectors:

$$\underset{(Z\times 1)}{\boldsymbol{z}_{i,t}} = [\ \mathrm{INF}_{i,t} \quad \mathrm{UN}_{i,t} \quad \mathrm{BILL}_{i,t} \quad \mathrm{NOTE}_{i,t} \quad \mathrm{BOND}_{i,t} \quad \mathrm{DP}_{i,t} \quad \mathrm{PE}_{i,t} \quad \mathrm{SRET12}_{i,t} \quad \mathrm{IV}_{i,t} \quad \mathrm{IS}_{i,t}\ ]', \tag{2}$$

$$\underset{(G\times 1)}{\boldsymbol{g}_{t}} = [\ \mathrm{EPU}_{t} \quad \mathrm{MPU}_{t} \quad \mathrm{GR}_{t} \quad \mathrm{GVOL}_{t} \quad \mathrm{GILL}_{t} \quad \mathrm{GCOR}_{t}\ ]', \tag{3}$$

respectively, for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, where N (T) is the number of countries (time-series observations). The vector of predictors for country i is comprised of the country characteristics and the characteristics interacted with each global variable:

$$\underset{(K\times 1)}{\boldsymbol{x}_{i,t}} = [\ \boldsymbol{z}_{i,t}' \quad \boldsymbol{h}_{i,t}'\ ]', \tag{4}$$

where

$$\underset{(ZG\times 1)}{\boldsymbol{h}_{i,t}} = \boldsymbol{z}_{i,t} \otimes \boldsymbol{g}_t, \tag{5}$$

$\otimes$ is the Kronecker product, and $K = Z(G+1)$. Since $Z = 10$ and $G = 6$ in Equations (2) and (3), respectively, we have $K = 70$ predictors for each country. We standardize each of

able at the time of forecast formation when fitting the autoregressive processes and computing the residuals. Bakshi and Panayotov (2013) and Filippou and Taylor (2017) use aggregated country characteristics and global variables to predict conventional carry trade portfolio returns, while we forecast individual exchange rate changes.

the country-i predictors using its county-specific mean and variance:

$$\tilde{\boldsymbol{x}}_{i,t} = (\boldsymbol{x}_{i,t} - \bar{\boldsymbol{x}}_{i\cdot}) \oslash \hat{\boldsymbol{\sigma}}_{i\cdot}, \tag{6}$$

where

$$\bar{\boldsymbol{x}}_{i\cdot} = \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{x}_{i,t}, \tag{7}$$

$$\hat{\boldsymbol{\sigma}}_{i\cdot} = \left[\frac{1}{T-1}\sum_{t=1}^{T}(\boldsymbol{x}_{i,t} - \bar{\boldsymbol{x}}_{i\cdot})^2\right]^{0.5}, \tag{8}$$

$\oslash$ indicates element-wise division, and the power operations in Equation (8) are element-wise. The panel predictive regression is given by

$$\Delta s_{i,t+1} = \tilde{\boldsymbol{x}}_{i,t}'\boldsymbol{b} + \varepsilon_{i,t+1} \quad \text{for } i = 1, \dots, N;\ t = 1, \dots, T, \tag{9}$$

where $\boldsymbol{b} = [\ b_1 \ \ \cdots \ \ b_K\ ]'$ is the K-vector of slope coefficients and $\varepsilon_{i,t}$ is a zero-mean disturbance term. Observe that Equation (9) does not include an intercept term. Because the predictors are in deviation form, this means that we effectively impose the economic restrictions that the country-specific means for $\Delta s_{i,t}$ for $i = 1, \dots, N$ are zero.[14] These economic restrictions are consistent with the data and reduce the number of parameters we need to estimate, thereby helping to guard against overfitting. The slope homogeneity restrictions inherent in Equation (9) further reduce the parameter space to again guard against overfitting.

It is convenient to express the panel predictive regression in matrix notation as

$$\Delta \boldsymbol{s} = \tilde{\boldsymbol{X}}\boldsymbol{b} + \boldsymbol{\varepsilon}, \tag{10}$$

[14] In other words, Equation (9) is tantamount to a fixed-effects specification in which the country-specific means for the log exchange rate changes are all zero.

where

$$\underset{(NT\times 1)}{\Delta \boldsymbol{s}} = [\ \Delta \boldsymbol{s}'_{1\cdot} \quad \cdots \quad \Delta \boldsymbol{s}'_{N\cdot}\ ]', \tag{11}$$

$$\underset{(T\times 1)}{\Delta \boldsymbol{s}_{i\cdot}} = [\ \Delta s_{i,2} \quad \cdots \quad \Delta s_{i,T+1}\ ]', \tag{12}$$

$$\underset{(NT\times K)}{\tilde{\boldsymbol{X}}} = [\ \tilde{\boldsymbol{X}}'_{1\cdot} \quad \cdots \quad \tilde{\boldsymbol{X}}'_{N\cdot}\ ]', \tag{13}$$

$$\underset{(T\times K)}{\tilde{\boldsymbol{X}}_{i\cdot}} = [\ \tilde{\boldsymbol{x}}_{i,1} \quad \cdots \quad \tilde{\boldsymbol{x}}_{i,T}\ ]', \tag{14}$$

$$\underset{(NT\times 1)}{\boldsymbol{\varepsilon}} = [\ \boldsymbol{\varepsilon}'_{1\cdot} \quad \cdots \quad \boldsymbol{\varepsilon}'_{N\cdot}\ ]', \tag{15}$$

$$\underset{(T\times 1)}{\boldsymbol{\varepsilon}_{i\cdot}} = [\ \varepsilon_{i,2} \quad \cdots \quad \varepsilon_{i,T+1}\ ]'. \tag{16}$$

For simplicity, we assume a balanced panel in the notation. When we estimate $\boldsymbol{b}$ in Equation (10) for our application, we have an unbalanced panel at some points; it is straightforward to adjust the notation accordingly. Note that we include more predictors than existing studies of exchange rate predictability, which typically consider a only limited number of country characteristics. In addition to numerous country characteristics, we include interactions of the country characteristics with a set of global variables. To the best of our knowledge, such interactions have not been considered in the literature on out-of-sample exchange rate predictability.

An out-of-sample forecast of $\Delta s_{i,T+1}$ based on the panel predictive regression in Equation (9) and data available through T is given by

$$\widehat{\Delta s}_{i,T+1|T} = \tilde{\boldsymbol{x}}'_{i,T}\hat{\boldsymbol{b}}_{1:T}, \tag{17}$$

where $\hat{\boldsymbol{b}}_{1:T}$ is an estimate of $\boldsymbol{b}$ based on data available through T. Because the panel predictive regression is high dimensional and the unpredictable component in monthly exchange rate changes is inherently large, conventional OLS estimation of $\boldsymbol{b}$ is susceptible to overfitting.

The ENet (Zou and Hastie 2005), a refinement of the popular LASSO (Tibshirani 1996), is a machine learning technique based on penalized (or regularized) regression. It mitigates overfitting by including a penalty term in the objective function for estimating $\boldsymbol{b}$ in Equation (10):

$$\underset{\boldsymbol{b}\in\mathbb{R}^K}{\arg\min}\ \frac{1}{2NT}\|\Delta\boldsymbol{s}-\tilde{\boldsymbol{X}}\boldsymbol{b}\|_2^2+\lambda P_\alpha(\boldsymbol{b}), \tag{18}$$

where $\lambda \geq 0$ is a regularization hyperparameter governing the degree of shrinkage,

$$P_\alpha(\boldsymbol{b}) = 0.5(1-\alpha)\|\boldsymbol{b}\|_2^2+\alpha\|\boldsymbol{b}\|_1, \tag{19}$$

α is a blending hyperparameter for the ℓ_1 and ℓ_2 components of the penalty term, and

$$\|\boldsymbol{v}\|_1 = \sum_{j=1}^{J}|v_j|, \tag{20}$$

$$\|\boldsymbol{v}\|_2 = \left(\sum_{j=1}^{J}v_j^2\right)^{0.5} \tag{21}$$

are the ℓ_1 and ℓ_2 norms, respectively, for a generic J-dimensional vector $\boldsymbol{v} = [\ v_1 \ \ \cdots \ \ v_J\ ]'$. When $\lambda = 0$, there is no shrinkage, so that the LASSO and OLS objective functions coincide. The ENet penalty term in Equation (18) includes both ℓ_1 (LASSO) and ℓ_2 (ridge) components. The ℓ_1 component permits shrinkage to zero (for sufficiently large λ), so that the LASSO performs variable selection.[15] Following the recommendation of Hastie and Qian (2016), we set $\alpha = 0.5$.

Instead of conventional cross validation, we tune the hyperparameter λ via the ERIC (Hui, Warton, and Foster 2015):

$$\text{ERIC} = NT \log\left(\frac{\text{SSR}_{\lambda,\alpha}}{NT}\right) + \text{df}_{\lambda,\alpha} \log\left(\frac{NT\hat{\sigma}^2_{\lambda,\alpha}}{\lambda}\right), \tag{22}$$

where $\text{SSR}_{\lambda,\alpha}$ ($\text{df}_{\lambda,\alpha}$) is the sum of squared residuals (effective degrees of freedom) for the ENet-fitted model based on λ and α, and $\hat{\sigma}^2_{\lambda,\alpha} = \text{SSR}_{\lambda,\alpha}/(NT)$. Equation (22) modifies the penalty term in the BIC to include λ. Considering a grid of values for λ, we select the value that minimizes Equation (22). The ERIC is a stringent information criterion that effectively induces substantive shrinkage, thereby helping to guard against overfitting in our high-dimensional and noisy data environment.[16]

3.2. Deep Neural Network

To this point, we permit a degree of nonlinearity in the predictive regressions via the interaction terms involving the country characteristics multiplied by the global variables; however, the specification in Equation (9) remains linear in the parameters. In this section, we allow for more complex predictive relationships by generalizing the linear specification in

[15] We implement elastic net estimation of the linear model in Equation (9) via the `glmnet` package in `R`. The LASSO is adept at selecting relevant predictors in some settings (e.g., Zhang and Huang 2008; Bickel, Ritov, and Tsybakov 2009; Meinshausen and Yu 2009). However, it tends to arbitrarily select one predictor from a group of highly correlated predictors. The ENet alleviates this tendency by including both ℓ_1 and ℓ_2 components in the penalty term for the objective function.

[16] Section A2 of the Internet Appendix discusses different validation methods for tuning λ in Equation (18), including conventional M-fold cross validation. As shown in Table A1 of the Internet Appendix, forecasts based on the ERIC generally perform better than those based on the different validation methods, as well as the BIC.

Equation (9):

$$\Delta s_{i,t+1} = f(\tilde{\boldsymbol{x}}_{i,t}) + \varepsilon_{i,t+1} \quad \text{for } i = 1, \ldots, N;\ t = 1, \ldots, T. \tag{23}$$

We then model $f(\tilde{\boldsymbol{x}}_{i,t})$ via a DNN, a popular machine learning device.

A feedforward neural network architecture is comprised of multiple layers. The first is the *input* layer, which is simply the set of predictors, which we denote by $x_1, \ldots, x_{K_0}$. One or more *hidden* layers are next. Each hidden layer l contains K_l neurons, each of which takes predictive signals from the neurons in the previous hidden layer to produce another signal:

$$h_m^{(l)} = g\left(\omega_{m,0}^{(l)} + \sum_{j=1}^{K_{l-1}} \omega_{m,j}^{(l)} h_j^{(l-1)}\right) \quad \text{for } m = 1, \ldots, K_l;\ l = 1, \ldots, L, \tag{24}$$

where $h_m^{(l)}$ is the mth neuron in the lth hidden layer;[17] $\omega_{m,0}^{(l)}, \ldots, \omega_{m,K_{l-1}}^{(l)}$ are weights; and $g(\cdot)$ is an activation function. The *output* layer is a linear function that translates the signals from the last hidden layer into a prediction:

$$\widehat{y} = \omega_0^{(L+1)} + \sum_{j=1}^{K_L} \omega_j^{(L+1)} h_j^{(L)}, \tag{25}$$

where $\widehat{y}$ denotes the forecast of the target variable. For the activation function, we use the leaky rectified linear unit (LReLU) function (Maas, Hannun, and Ng 2013):[18]

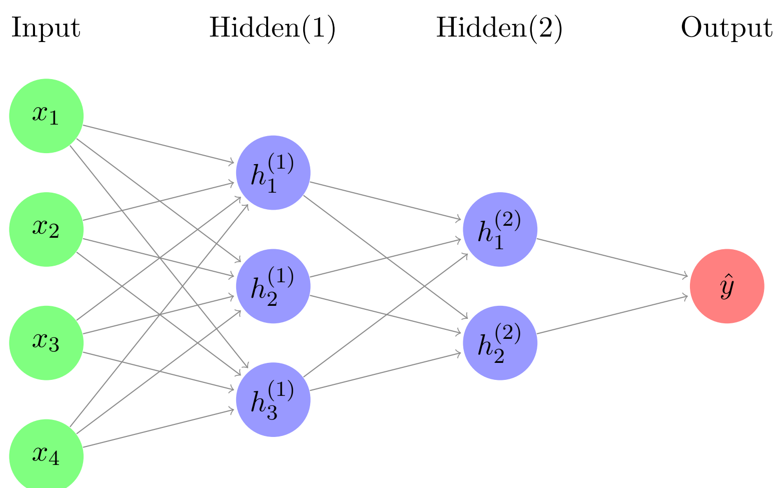
$$g(x) = \begin{cases} x & \text{if } x > 0, \\ 0.01x & \text{if } x \leq 0. \end{cases} \tag{26}$$

[17]For the first hidden layer, $h_j^{(0)} = x_j$ for $j = 1, \ldots, K_0$.

[18]The LReLU refines the conventional ReLU (which sets $g(x) = 0$ if $x \leq 0$) to help prevent the DNN from "dying" during training, meaning that the neurons in the DNN never activate.

Intuitively, Equation (26) activates a neuronal connection in response to the strength of the signal, thereby relaying the signal forward through the network.

The following diagram provides a schematic for a relatively simple feedforward neural network architecture with four predictors and two hidden layers, where the hidden layers contain three and two neurons, respectively. The diagram shows that the four predictors in the input layer feed through to provide signals to each of the three neurons in the first hidden layer; the neurons in the first hidden layer subsequently feed through to provide signals to each of the two neurons in the second hidden layer. The neurons in the second hidden layer provide a final set of signals for the output layer.



Theoretically, a neural network with a single hidden layer and sufficiently large number of neurons can approximate any smooth function under a reasonable set of assumptions (e.g., Cybenko 1989; Funahashi 1989; Hornik, Stinchcombe, and White 1989; Hornik 1991; Barron 1994). However, neural networks with three or more hidden layers (i.e., DNNs) and a more limited number of neurons in each layer often perform better than neural networks with one or two hidden layers (i.e., shallow neural networks) and a larger number of neurons in each layer (e.g., Goodfellow, Bengio, and Courville 2016; Rolnick and Tegmark 2018). We specify a DNN containing four hidden layers with 16, eight, four, and two neurons, respectively. Our specification of 16 neurons in the first hidden layer is a compromise between two popular rules of thumb, namely, half or the square root of the number of predictors.

Training a DNN entails estimating the weights. We estimate the weights by minimizing an objective function based on MSPE for the training sample. To better guard against overfitting, we augment the objective function with ℓ_1 and ℓ_2 penalty terms, similarly to Equation (18). Computationally efficient algorithms based on stochastic gradient descent (SGD) are available for estimating the DNN weights. We use the recently developed Adam algorithm (Kingma and Ba 2015).[19]

Given our noisy data environment, we take additional steps to further guard against overfitting. First, we set the intercept terms for the weights ($\omega_{m,0}^{(l)}$ for $m = 1, \ldots, K_l$; $l = 1, \ldots, L$ and $\omega_0^{(L+1)}$) to zero.[20] These economic restrictions are analogous to the absence of an intercept term in the linear panel predictive regression in Equation (9). By setting the intercept terms for the weights to zero, as in Equation (9), we ensure that the DNN predicts a value of zero for the exchange rate change when all of the (standardized) predictors are at their mean value of zero.[21] These restrictions substantially reduce the number of weights we need to estimate, thereby helping to guard against overfitting. Second, we employ dropout (Hinton et al. 2012; Srivastava et al. 2014), which randomly drops a portion of the neurons in a hidden layer when training the model via the SGD algorithm. Dropout has been found to be useful for mitigating overfitting. We use a dropout rate of 0.5 for each of the first three hidden layers.

[19] We estimate the DNN using the `keras` package in `R` and set the batch size and number of epochs to 32 and 500, respectively. Due to the stochastic nature of the SGD algorithm, the estimated weights depend on the seed for the random number generator. To reduce the dependency of the DNN forecast on the seed, we train the model three different times with different seeds and take an average of the forecasts across the three fitted DNNs. To tune the ℓ_1 and ℓ_2 regularization hyperparameters for the DNN, we consider a grid of values for each and use observations for the last 30% of months for the available data at the time of forecast formation as a validation sample. We select the vector of hyperparameter values that minimizes the objective function for the validation sample.

[20] The intercept terms for the weights are typically called "bias" terms in the machine learning literature, although bias does not have its traditional econometric meaning in this context.

[21] Note that we continue to pool the data in Equation (23), so that we impose the homogeneity restrictions that the weights are the same across countries.

4. Out-of-Sample Performance

In this section, we analyze the accuracy of the out-of-sample exchange rate forecasts. We also examine the importance of individual predictors in the forecasting models.

4.1. Beating the No-Change Benchmark

Mimicking the situation of a forecaster in real time, we generate exchange rate forecasts for the 1995:01 to 2020:09 out-of-sample period as follows. Reserving the first ten years of data for the initial training sample, we estimate the linear panel predictive regression in Equation (9) and DNN using data from the beginning of the available sample through 1994:12. We then use the fitted models and 1994:12 predictor values for each country to compute forecasts of exchange rate changes for each available country for 1995:01. Next, we re-estimate the models using data through 1995:01; we then use the fitted models and 1995:01 predictor values for each country to generate forecasts for each available country for 1995:02. We continue in this fashion through the end of the out-of-sample period, providing us with a set of exchange rate forecasts for the available countries for each of the 309 months comprising the out-of-sample period. Each month we compute Linear-OLS and Linear-ENet forecasts based on OLS and ENet estimation, respectively, of the linear specification in Equation (9), as well as forecasts based on the DNN. By retraining the forecasting models each month as new data become available, we update the fitted models in a timely manner. Note that there is no "look-ahead" bias in the forecasts, as we only use data available at the time of forecast formation when training the models.[22]

We also compute an ensemble forecast by taking the average of the Linear-ENet and DNN forecasts. An ensemble forecast recognizes that we cannot know a priori the best individual model. Furthermore, it allows us to take advantage of any complementarities between the

[22]This includes when we standardize the predictors in Equation (6).

models. To the best of our knowledge, we are the first to employ an ensemble strategy that combines linear and DNN models for exchange rate prediction.

For Germany, Italy, France, and the Netherlands, there are only 48 monthly forecasts (1995:01 to 1998:12) available for evaluation, due to the countries joining the Euro area in 1999:01. After imposing a minimum requirement of twelve monthly observations before a currency is included in the panel predictive regression, there are 248 forecasts (2000:02 to 2020:09) available for the Euro area. For the remaining nine countries, forecasts are available for the entire 1995:01 to 2020:09 out-of-sample period (309 observations). In addition to reporting results for each individual country, we report results for the entire collection of forecasts taken together ($4 \times 48 + 248 + 9 \times 309 = 3{,}221$ observations).

Figure 1 depicts the Linear-OLS forecasts, while Figures 2 and 3 show the Linear-ENet and DNN forecasts, respectively. The Linear-OLS forecasts are quite volatile, indicating substantive overfitting for conventional OLS estimation in our high-dimensional and noisy data environment. The Linear-ENet forecasts are considerably less volatile, reflecting the strong shrinkage property of the ENet with ERIC hyperparameter tuning. The DNN forecasts are also much less volatile than the Linear-OLS forecasts, in line with the steps we take to guard against overfitting, as described in Section 3.2.

Next, we compare the Linear-OLS, Linear-ENet, DNN, and ensemble forecasts to the no-change benchmark, which is the most stringent benchmark for exchange rate prediction (Rossi 2013). We assess the accuracy of the exchange rate forecasts in terms of MSPE. We can conveniently compare the relative accuracy of a competing forecast to the no-change benchmark using the Campbell and Thompson (2008) R^2_{OS} statistic:

$$R^2_{\text{OS}} = 1 - \frac{\sum_{t=T_1+1}^{T_2} \left(\hat{e}_{i,t|t-1}^{\text{Compete}} \right)^2}{\sum_{t=T_1+1}^{T_2} \left(\hat{e}_{i,t|t-1}^{\text{Bench}} \right)^2}, \tag{27}$$

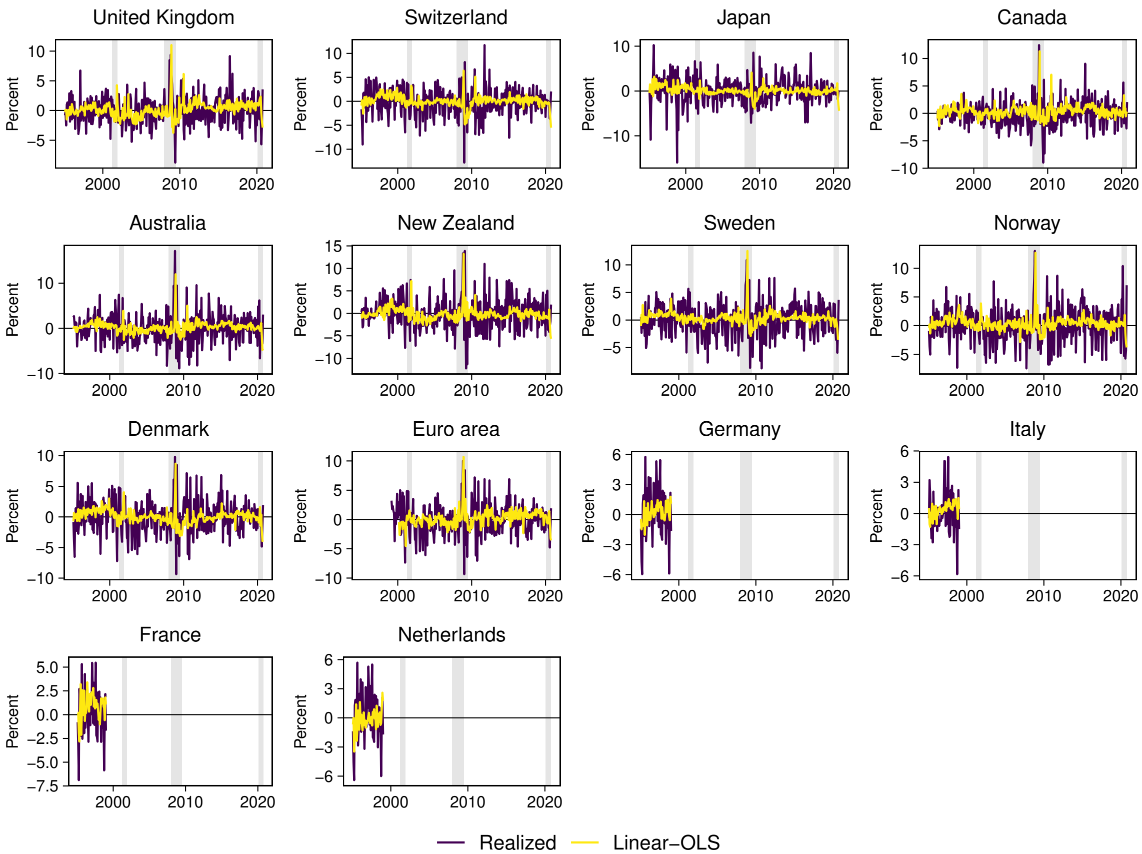


Figure 1. Linear-OLS forecasts of log exchange rate changes. Each panel depicts the realized value and Linear-OLS forecast for the monthly log exchange rate change for the country in the panel heading. Vertical bars delineate business-cycle recessions as dated by the National Bureau of Economic Research.

where

$$\hat{e}^{\text{Compete}}_{i,t|t-1} = \Delta s_{i,t} - \widehat{\Delta s}^{\text{Compete}}_{i,t|t-1}, \tag{28}$$

$$\hat{e}^{\text{Bench}}_{i,t|t-1} = \Delta s_{i,t} - \underbrace{\widehat{\Delta s}^{\text{Bench}}_{i,t|t-1}}_{=0}, \tag{29}$$

$\widehat{\Delta s}^{\text{Bench}}_{i,t|t-1} = 0$ is the no-change benchmark forecast, $\widehat{\Delta s}^{\text{Compete}}_{i,t|t-1}$ is a competing forecast (Linear-OLS, Linear-ENet, DNN, or ensemble), T_1 is the last observation for the initial in-sample

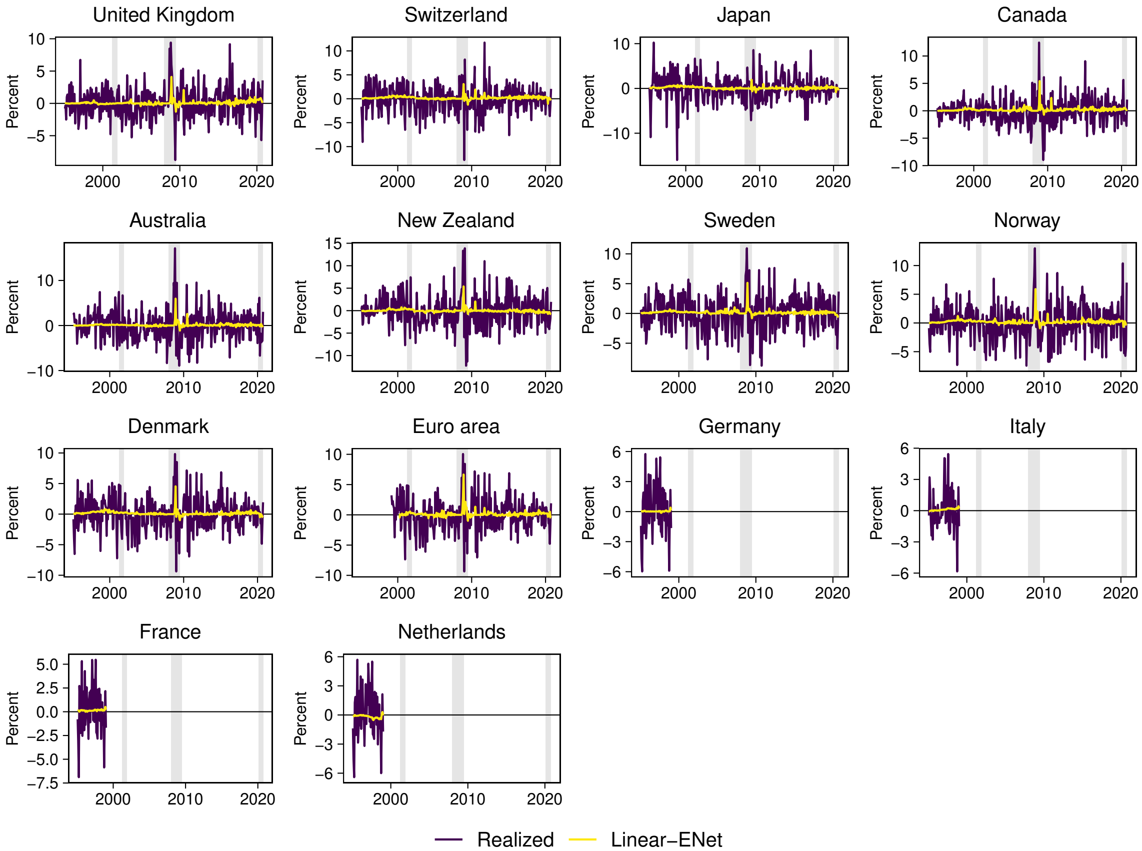


Figure 2. Linear-ENet forecasts of log exchange rate changes. Each panel depicts the realized value and Linear-ENet forecast for the monthly log exchange rate change for the country in the panel heading. Vertical bars delineate business-cycle recessions as dated by the National Bureau of Economic Research.

period, and T_2 is the last available observation for the out-of-sample period.[23] The R^2_{OS} statistic measures the proportional reduction in MSPE for a competing forecast vis-à-vis the benchmark. Because the predictable component in monthly exchange rate changes is intrinsically small, the R^2_{OS} statistic will necessarily be small. Nevertheless, even a seemingly small degree of monthly exchange rate predictability can be economically meaningful, as we show in Section 5 below and as is the case for stock return predictability (Campbell and Thompson 2008). To get a sense of whether the competing forecast provides a statistically

[23]For our application, T_1 and T_2 correspond to 1994:12 and 2020:09, respectively.

significant improvement in MSPE relative to the benchmark, we compute the Clark and West (2007) adjusted version of the Diebold and Mariano (1995) and West (1996) statistic.[24]

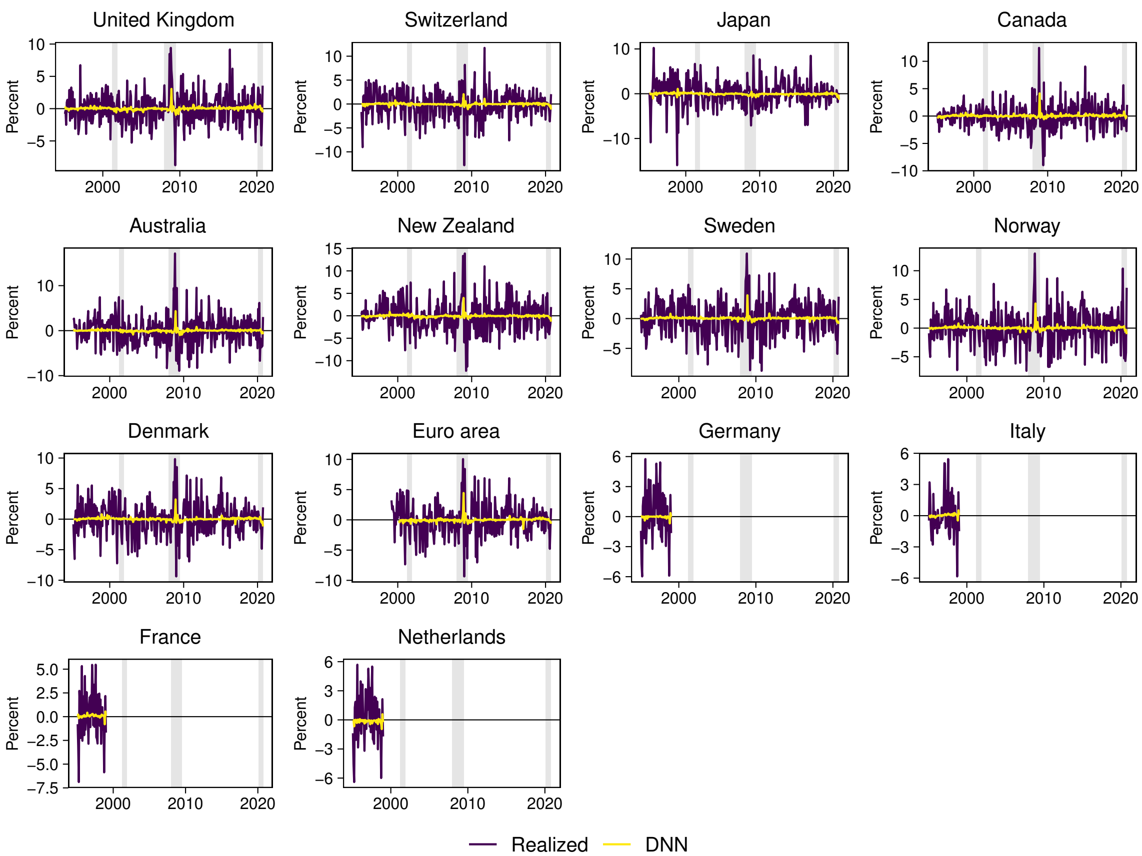


Figure 3. Deep neural network forecasts of log exchange rate changes. Each panel depicts the realized value and DNN forecast for the monthly log exchange rate change for the country in the panel heading. Vertical bars delineate business-cycle recessions as dated by the National Bureau of Economic Research.

Table 2 reports R^2_{OS} statistics for the Linear-OLS, Linear-ENet, DNN, and ensemble forecasts. The R^2_{OS} statistics are all negative in the fourth column of Table 2, so that the

[24] As shown by Clark and McCracken (2001) and McCracken (2007), the Diebold-Mariano-West statistic has a non-standard asymptotic distribution when comparing forecasts from nested models (as is the case for our application). In particular, the Diebold-Mariano-West statistic can be severely undersized when comparing nested forecasts, meaning that it can have little power to detect a significant improvement in forecast accuracy.

Linear-OLS forecasts always fail to outperform the no-change benchmark in terms of MSPE. The negative R^2_{OS} statistics are often sizable in magnitude for the individual countries, and the statistic is -9.21% for all of the countries taken together in the last row. The overfitting in the Linear-OLS forecast suggested by Figure 1 thus translates into poor out-of-sample performance in terms of forecast accuracy in Table 2.

As shown in the fifth column of Table 2, the Linear-ENet forecasts evince markedly better out-of-sample performance. The R^2_{OS} statistics are positive for twelve of the 14 countries, and the reductions in MSPE vis-à-vis the no-change benchmark are significant at conventional levels for seven of the counties. Eight of the R^2_{OS} statistics for the individual countries are above 1% and reach as high as 2.88% (Sweden), so that they are sizable in the context of the literature surveyed by Rossi (2013). For the complete set of countries taken together in the last row, the R^2_{OS} statistic is 1.48% (significant at the 1% level). According to the sixth column, the DNN forecasts also perform well. The R^2_{OS} statistics are positive for 13 of the 14 countries, including all ten of the G10 countries (for which at least 248 out-of-sample observations are available); the improvements in MSPE are significant for nine of the G10 countries (as well as Italy). The R^2_{OS} statistics for the individual countries are sizable, as eleven (five) are above 1% (2%). Taking all of the countries together, the R^2_{OS} statistic is 1.85% (significant at the 1% level) in the last row.

By combining the Linear-ENet and DNN forecasts, the ensemble approach in the last column of Table 2 provides the best overall performance. The R^2_{OS} statistics are positive for all of the countries, and the improvements in MSPE vis-à-vis the no-change benchmark are significant at conventional levels for nine of the countries. The R^2_{OS} statistics are also typically sizable, with ten (six) above 1% (2%) and as large as 3.12% (United Kingdom). For the entire set of countries taken together, the R^2_{OS} statistic is 1.88% (significant at the 1% level), which is the highest value in the last row of Table 2. Note that the R^2_{OS} statistics for the ensemble forecasts are often larger or nearly as large as the highest corresponding

Table 2: R^2_{OS} Statistics (%)

The table reports Campbell and Thompson (2008) R^2_{OS} statistics in percent for forecasts of monthly log exchange rate changes. The country-i log exchange rate change is $\Delta s_{i,t}$, where $s_{i,t} = \log(S_{i,t})$ and $S_{i,t}$ is the month-t spot exchange rate for country i (number of country-i currency units per US dollar). The R^2_{OS} statistic measures the proportional reduction in MSPE for the competing forecast in the column heading vis-à-vis the no-change benchmark forecast; for the positive R^2_{OS} statistics, *, **, and *** indicate that the reduction in MSPE is significant at the 10%, 5%, and 1% levels, respectively, according to the Clark and West (2007) test. The Linear-OLS, Linear-ENet, DNN, and ensemble forecasts incorporate the information in 70 predictors.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Country	Out-of-Sample Period	Obs.	Linear-OLS	Linear-ENet	DNN	Ensemble
United Kingdom	1995:01–2020:09	309	−12.08	2.77*	2.95**	3.12**
Switzerland	1995:01–2020:09	309	−13.40	1.03	2.65**	2.11**
Japan	1995:01–2020:09	309	−11.31	−0.25	1.30*	0.75*
Canada	1995:01–2020:09	309	−19.15	−0.40	0.60	0.42
Australia	1995:01–2020:09	309	−4.30	1.04*	1.60***	1.48**
New Zealand	1995:01–2020:09	309	−7.77	1.90*	2.16**	2.16**
Sweden	1995:01–2020:09	309	−3.87	2.88**	2.57**	2.86**
Norway	1995:01–2020:09	309	−3.26	2.45**	1.69**	2.27**
Denmark	1995:01–2020:09	309	−6.57	2.23***	1.76***	2.18***
Euro area	2000:02–2020:09	248	−13.24	1.12*	1.48**	1.75**
Germany	1995:01–1998:12	48	−11.68	0.45	−0.16	0.23
Italy	1995:01–1998:12	48	−13.37	0.24	2.36*	1.40
France	1995:01–1998:12	48	−37.73	0.62	1.47	1.18
Netherlands	1995:01–1998:12	48	−20.73	0.88	0.32	0.82
All	1995:01–2020:09	3,221	−9.21	1.48***	1.85***	1.88***

statistics in the fifth and sixth columns, pointing to meaningful complementarities in the linear and nonlinear forecasts.[25]

[25]Forecasts generated by estimating models using country-specific data are less accurate than forecasts based on pooling, so that the parameter homogeneity restrictions improve out-of-sample performance.

To examine the performance of the Linear-ENet, DNN, and ensemble forecasts over time, Figure 4 employs the graphical device of Goyal and Welch (2003, 2008). The figure portrays cumulative differences in squared prediction error for the no-change benchmark vis-à-vis the Linear-ENet, DNN, and ensemble forecasts (in turn). Each curve conveniently allows for a comparison of forecast accuracy (in terms of MSPE) for any subsample: we compare the height of the curve at the beginning and end of the segment corresponding to the subsample; if the curve is higher (lower) at the end of the segment, then the competing (benchmark) forecast has a lower MSPE for the subsample. A forecast that always outperforms the benchmark will thus have a curve with a uniformly positive slope. Of course, given that exchange rate changes have a large unpredictable component, this ideal is unattainable in practice. Realistically, we seek a forecast with a curve that is predominantly positively sloped and does not have extended segments with negative slopes.

According to Figure 4, the curves are positively sloped for much of the time for the different countries—especially the G10 countries—so that the Linear-ENet, DNN, and ensemble forecasts outperform the no-change benchmark on a reasonably consistent basis over time. By blending the Linear-ENet and DNN forecasts, the ensemble approach generally provides the most consistent out-of-sample gains. The improvements in accuracy provided by the Linear-ENet, DNN, and ensemble forecasts vis-à-vis the no-change benchmark are particularly strong during the worst phase of the global financial crisis in late 2008, so that the information in the predictors becomes especially important during the crisis. Sizable gains are evident before the crisis in a number of cases, and the gains are quite consistent for many countries after 2008 through the end of the out-of-sample period. Compared to the Linear-ENet forecasts, the DNN forecasts substantially improve performance around the crisis for Switzerland, Japan, and Canada. Overall, Table 2 and Figure 4 indicate that the information in a rich set of predictors can be used to generate sizable and consistent improvements in out-of-sample forecasting accuracy, provided we adequately guard against overfitting in our high-dimensional and noisy data setting.

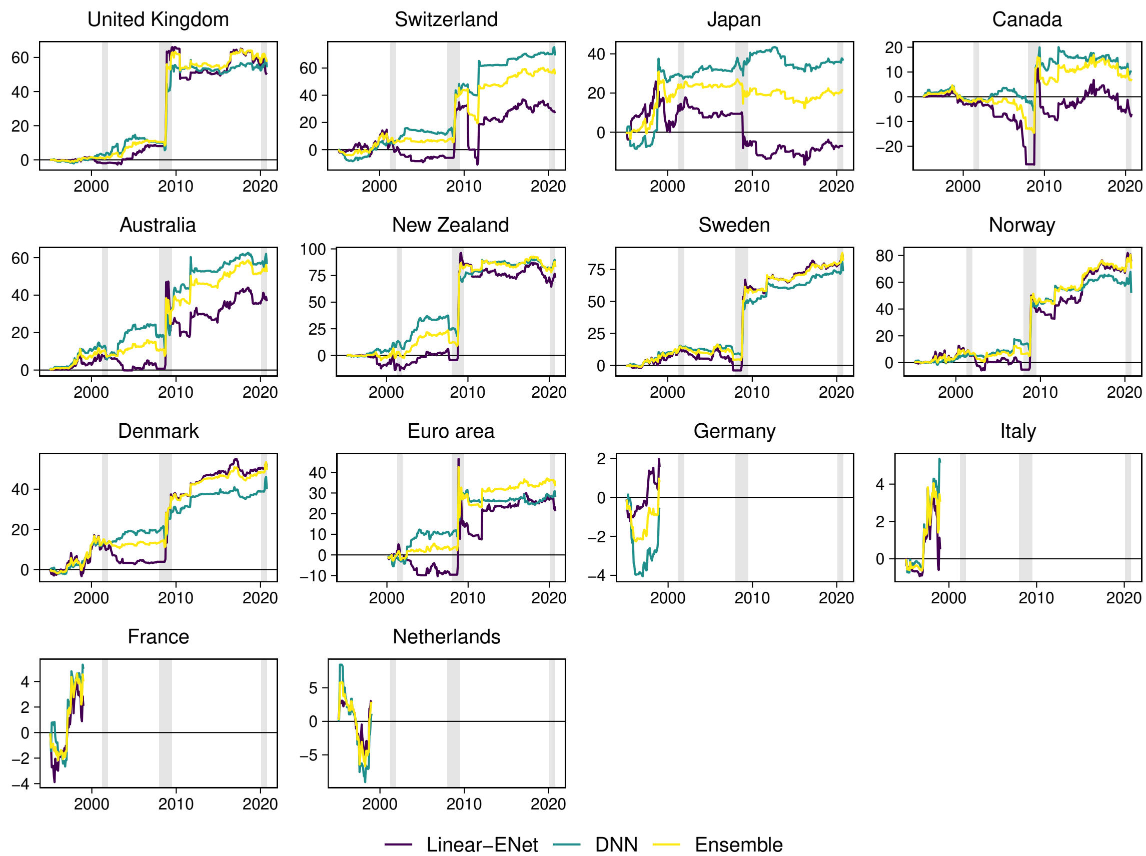


Figure 4. Cumulative differences in squared prediction error. Each panel depicts the cumulative difference in squared prediction error for the log exchange rate change for the country in the panel heading. The difference is computed for the no-change benchmark relative to the Linear-ENet, DNN, and ensemble forecasts (in turn). Vertical bars delineate business-cycle recessions as dated by the National Bureau of Economic Research.

4.2. Which Predictors Matter?

It is of economic interest to know the importance of the individual predictors in the models underlying the forecasts. To this end, we compute variable importance measures for the fitted models via the approach of Greenwell, Boehmke, and McCarthy (2018), which is based on PDPs (Friedman 2001). PDPs themselves are interesting, as they allow us to investigate the strength of nonlinearities in fitted models.

A PDP examines the relationship between the expected value of the target variable and a given predictor for any fitted model, including "black-box" models like DNNs. Let $\hat{f}(\boldsymbol{x})$ denote the prediction function for a generic fitted model, where $\boldsymbol{x}$ denotes the vector of predictors. The PDP for x_q is defined as

$$\begin{aligned} f_q(x_q) &= E_{\boldsymbol{x}_{C(q)}}\left[\hat{f}\big(x_q, \boldsymbol{x}_{C(q)}\big)\right] \\ &= \int_{\boldsymbol{x}_{C(q)}} \hat{f}\big(x_q, \boldsymbol{x}_{C(q)}\big) p_{C(q)}\big(\boldsymbol{x}_{C(q)}\big)\, d\boldsymbol{x}_{C(q)}, \end{aligned} \tag{30}$$

where $\boldsymbol{x}_{C(q)} = \boldsymbol{x} \setminus x_q$ and

$$p_{C(q)}\big(\boldsymbol{x}_{C(q)}\big) = \int_{x_q} p(x_q, \boldsymbol{x}_{C(q)})\, dx_q \tag{31}$$

is the joint marginal probability density for $\boldsymbol{x}_{C(q)}$. Equation (30) is typically estimated via Monte Carlo integration using the training data, which in our panel data setting is given by

$$\bar{f}_q(x_q) = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{f}\big(x_q, \boldsymbol{x}_{i,t,C(q)}\big). \tag{32}$$

It is common to plot the PDP for a grid of x_q values in the range of training-sample observations, which we denote by $\{x_{q,j}\}_{j=1}^{J}$. By construction, the PDP is a straight line for a linear model.

Greenwell, Boehmke, and McCarthy (2018) propose a PDP-based measure of predictor importance:

$$\mathcal{I}(x_q) = \left\{ \left(\frac{1}{J-1} \right) \sum_{j=1}^{J} \left[\bar{f}_q(x_{q,j}) - \frac{1}{J} \sum_{j=1}^{J} \bar{f}_q(x_{q,j}) \right]^2 \right\}^{0.5}. \tag{33}$$

Intuitively, Equation (33) uses the sample standard deviation of the PDP to measure its "flatness."[26] If the expected value of the target does not change as the predictor changes, then the PDP is flat, so that the variable importance measure is zero. As the variability of the PDP increases, the importance measure in Equation (33) likewise increases.

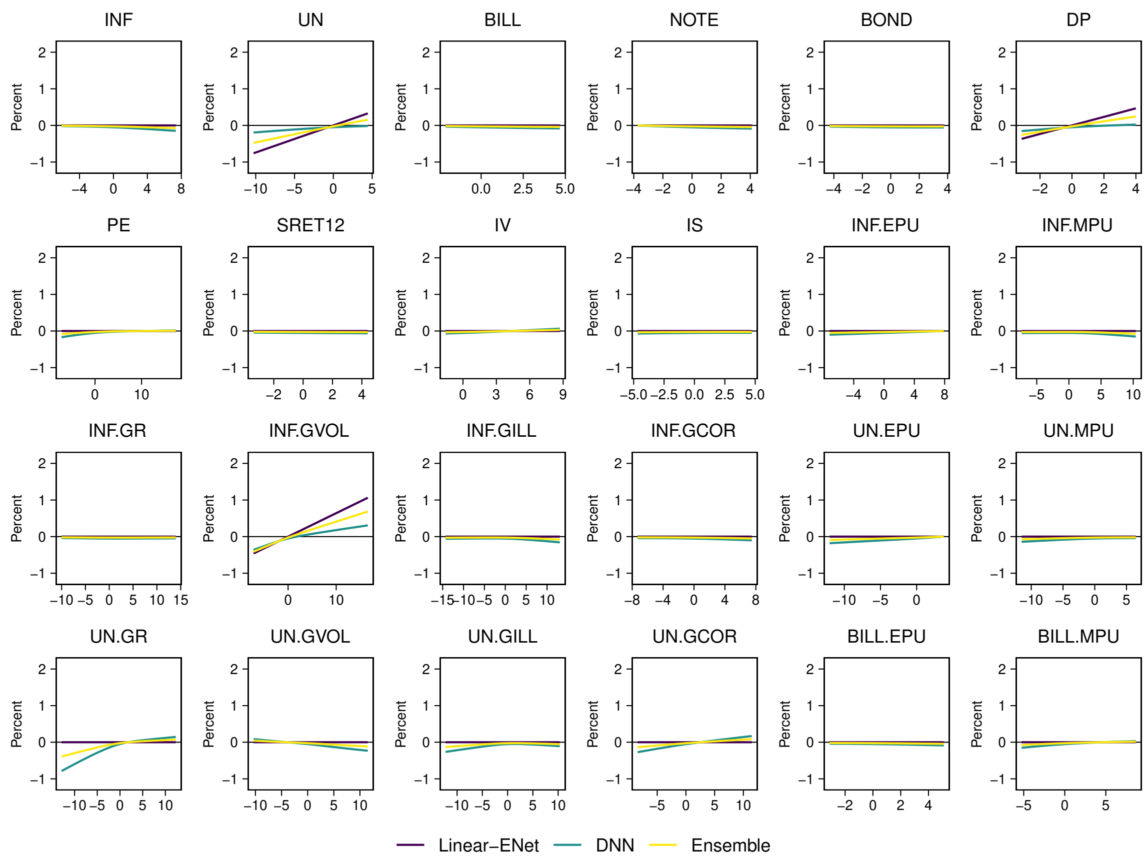


Figure 5. Partial dependence plots. Each panel depicts the partial dependence plot in Equation (32) for the predictor in the panel heading. Plots are provided for the fitted models underlying the Linear-ENet, DNN, and ensemble forecasts.

Figure 5 depicts PDPs based on Equation (32) for the fitted Linear-ENet and DNN models used to generate the final set of forecasts (for 2020:09), so that they are based on the longest training sample (data through 2020:08). The figure also shows PDPs for the

[26]We scale the variable importance measures so that they sum to one.

ensemble forecasts, which are averages of the PDPs for the fitted Linear-ENet and DNN models.[27] Figure 6 depicts corresponding variable importance measures computed using Equation (33).

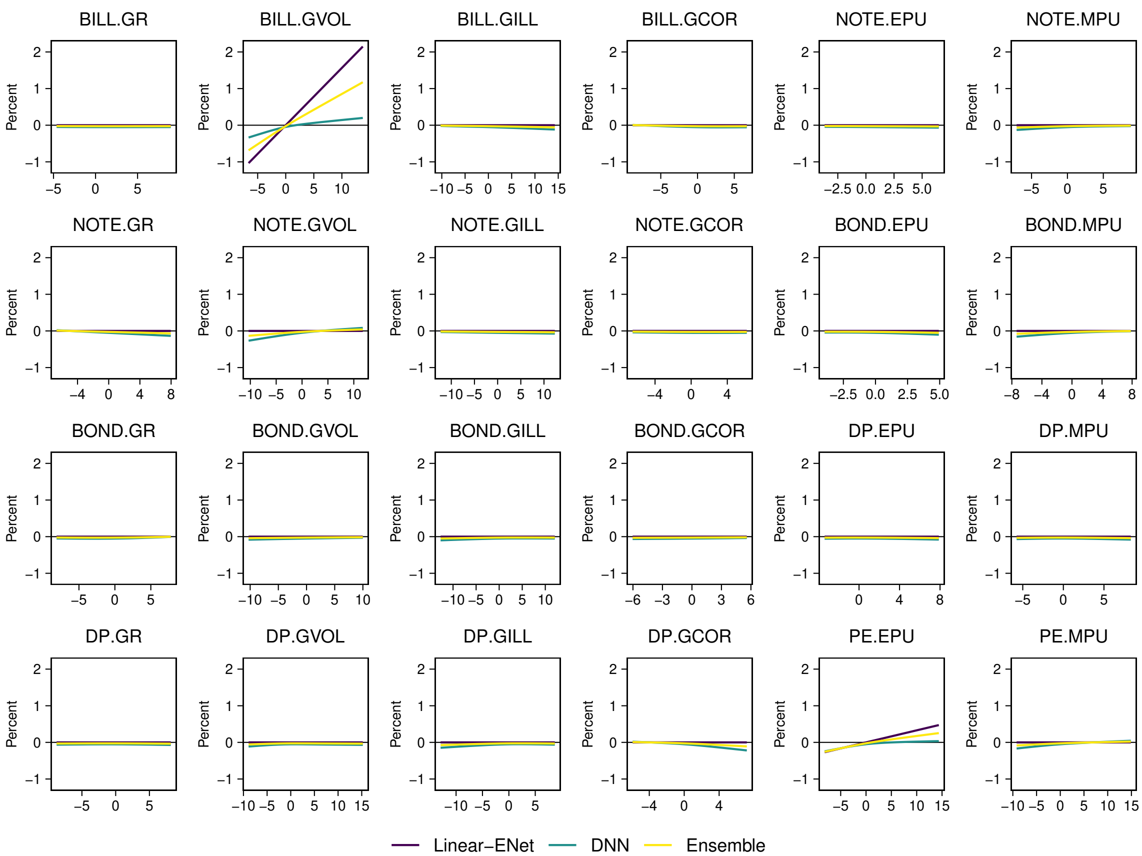


Figure 5 (continued).

For the predictors not selected by the ENet in the linear model, the PDP is a horizontal line at zero in Figure 5, which corresponds to a zero variable importance measure for these predictors in the first panel of Figure 6. For the Linear-ENet, eight of the 70 predictors are selected. According to Figure 6, BILL.GVOL is the most important variable in the Linear-ENet, followed by IV.GCOR, INF.GVOL, PE.GILL, UN, SRET12.MPU, DP, and PE.EPU.

[27] We denote predictors that are the interaction between two variables with a period between the two variables; for example, the interaction between INF and EPU is INF.EPU.

These predictors are also typically important in the DNN and ensemble in the second and third panels, respectively, of Figure 6. A number of additional predictors appear relatively important in the DNN and ensemble, including some of the interaction terms involving UN (UN.GR, UN.GVOL, and UN.GCOR).

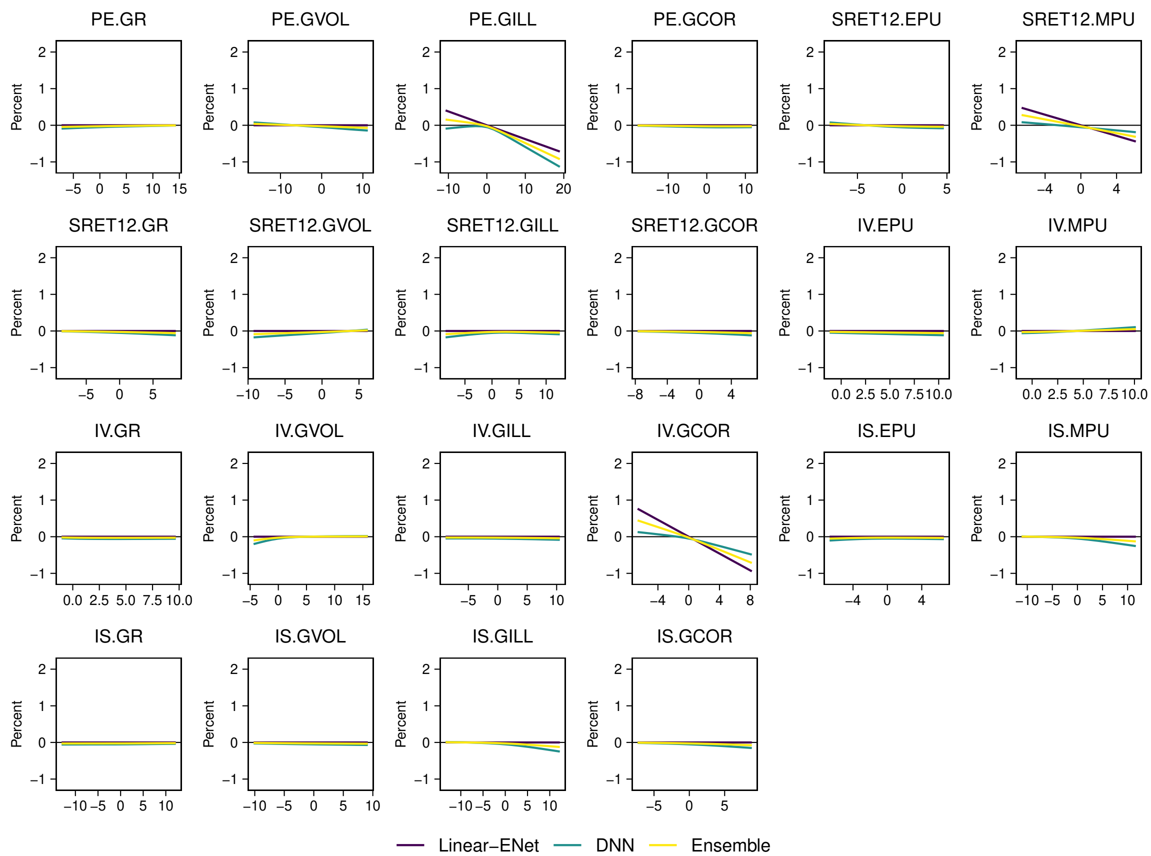


Figure 5 (continued).

As shown in in Figure 5, for a number of predictors not selected by the Linear-ENet, the PDPs for the DNN are essentially horizontal lines at zero, which translate into near zero values for the variable importance measures in Figure 6, so that these predictors are unimportant in both the Linear-ENet and DNN. For UN, DP, INF.GVOL, BILL.GVOL, SRET12.MPU, and IV.GCOR, the PDPs for the Linear-ENet and DNN are both essentially linear, although the slopes for the Linear-ENet are considerably steeper those for the DNN.

For some other predictors that are relatively important in the DNN, the PDPs are also close to linear (e.g., UN.GVOL and UN.GCOR). Nonlinearities are more evident for the DNN for a number of other predictors in Figure 5. In these cases, the nonlinearities often manifest as stronger predictive relationships for more extreme positive or negative values for the predictors. Consider, for example, UN.GR. The PDP is essentially flat at zero for a wide range of values for the predictor, but it becomes more positively sloped for larger negative values (in magnitude).[28]

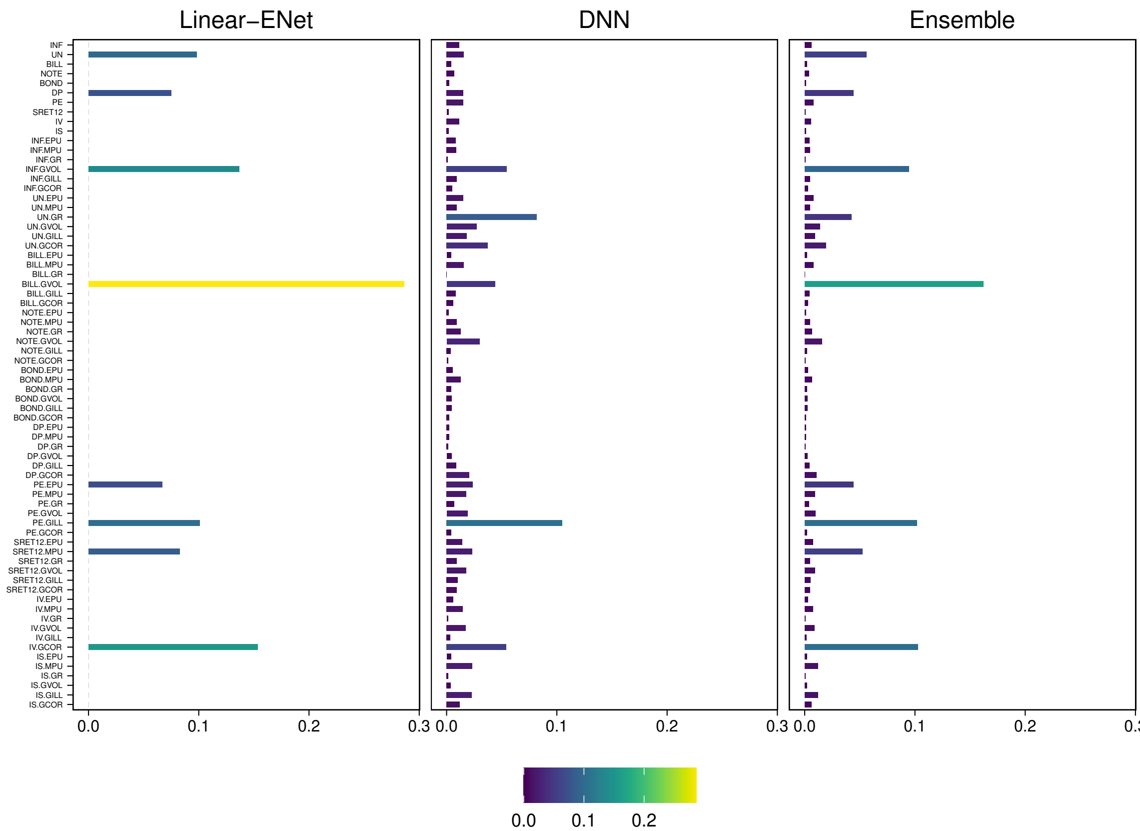


Figure 6. Variable importance. Each panel depicts variable importance measures for the individual predictors in the fitted model underlying the forecast in the panel heading.

[28]SHAP values (Lundberg and Lee 2017) and corresponding variable importance measures for the Linear-ENet, DNN, and ensemble are similar to the PDPs and variable importance measures in Figures 5 and 6, respectively.

INF and BILL are perhaps the most popular exchange rate predictors in the literature. Neither variable on its own is selected by the Linear-ENet, and both are of limited importance in the DNN. However, INF and BILL are quite important when they interact with GVOL, as INF.GVOL and BILL.GVOL are important predictors in all of the models in Figure 6. The PDPs for INF.GVOL and BILL.GVOL are positively sloped for both the Linear-ENet and DNN in Figure 5, so that the expected US dollar appreciation in response to an increase in INF or BILL becomes larger as GVOL increases. According to PPP, an increase in INF leads to an increase in expected US dollar appreciation, so that the prediction of PPP becomes more relevant as GVOL increases. Similarly, UIP predicts that an increase in BILL corresponds to an increase in expected US dollar appreciation, meaning that the relationship predicted by UIP holds to a greater degree as GVOL increases (as it does, e.g., during the global financial crisis). Overall, we find that popular fundamentals matter when they interact with global variables, especially global volatility.

An emerging literature (e.g., Engel and Wu 2019; Kremens and Martin 2019; Adrian and Xie 2020; Jiang, Krishnamurthy, and Lustig 2021; Lilley et al. forthcoming) finds evidence of exchange rate predictability around the global financial crisis using variables related to the US dollar's safe-haven status. Based on data availability, these studies use relatively short samples and/or analyze medium- to long-horizon predictability (horizons of one quarter to multiple years). In contrast, we consider a lengthy out-of-sample period (beginning well before the global financial crisis and extending to 2020:09) and focus on short-horizon (monthly) predictability. As discussed in Section A3 of the Internet Appendix, our results are consistent with exchange rate predictability during the crisis corresponding to the US dollar's safe-haven role.

5. Carry Trade Portfolios

In this section, we analyze the economic value of the Linear-ENet, DNN, and ensemble forecasts in the context of carry trade portfolios.

5.1. Portfolio Construction

We consider a US investor with mean-variance preferences who allocates monthly across available foreign currencies. At the end of month T, the investor's objective function is given by

$$\max_{\boldsymbol{w}_{T+1|T}} \boldsymbol{w}'_{T+1|T}\hat{\boldsymbol{\mu}}_{T+1|T} - 0.5\gamma\boldsymbol{w}'_{T+1|T}\hat{\boldsymbol{\Sigma}}_{T+1|T}\boldsymbol{w}_{T+1|T}, \tag{34}$$

where

$$\hat{\boldsymbol{\mu}}_{T+1|T} = [\ \widehat{rx}_{1,T+1|T} \quad \cdots \quad \widehat{rx}_{N,T+1|T}\ ]', \tag{35}$$

$$\widehat{rx}_{i,T+1|T} = (r_{i,T} - r_{\text{US},T}) - \widehat{\Delta s}_{i,T+1|T}, \tag{36}$$

$r_{i,T}$ ($r_{\text{US},T}$) is the government bill yield for country i (the United States), $\widehat{\Delta s}_{i,T+1|T}$ ($\widehat{rx}_{i,T+1|T}$) is the investor's exchange rate change (currency excess return) forecast for country i, $\hat{\boldsymbol{\Sigma}}_{T+1|T}$ is the investor's estimate of the covariance matrix for the currency excess returns, $\boldsymbol{w}_{T+1|T} = [\ w_{1,T+1|T} \quad \cdots \quad w_{N,T+1|T}\ ]'$ is the N-vector of portfolio weights that will be in effect for month $T+1$, and γ is the coefficient of relative risk aversion. As is common among practitioners, we assume that the investor uses an exponentially weighted moving average (EWMA) estimator for $\hat{\boldsymbol{\Sigma}}_{T+1|T}$. We assume that $\gamma = 5$; the results are qualitatively similar for reasonable alternative γ values. In order to keep the portfolio weights in a plausible range, we also impose the restrictions that $-0.5 \leq w_{i,T+1|T} \leq 0.5$ for $i = 1, \ldots, N$.

We consider two cases, which differ with respect to the exchange rate forecast used to compute $\widehat{rx}_{i,T+1|T}$ in Equation (36). In the Smart-Opt case, the investor uses the Linear-ENet, DNN, or ensemble forecast for $\widehat{\Delta s}_{i,T+1|T}$ in Equation (36), so that they attempt to exploit exchange rate predictability when allocating across currencies. In the Basic-Opt case, the investor uses the no-change benchmark forecast ($\widehat{\Delta s}_{i,T+1|T} = 0$) in Equation (36), so that they ignore exchange rate predictability and simply use the bill yield differential (which is known at T) to predict the excess return.

We construct out-of-sample portfolio weights as follows. We first use data through 1994:12 to compute the EWMA estimate of the covariance matrix and Linear-ENet, DNN, or ensemble exchange rate forecasts for 1995:01. We then solve Equation (34) using the Linear-ENet, DNN, or ensemble (no-change) exchange rate forecasts to compute the Smart-Opt (Basic-Opt) portfolio weights for 1995:01. Next, we use data through 1995:01 to generate the EWMA covariance matrix estimate and Linear-ENet, DNN, or ensemble forecasts for 1995:02; we then compute the Smart-Opt and Basic-Opt portfolio weights for 1995:02. We proceed in this fashion through the end of the out-of-sample period, so that we mimic the situation of an investor in real time.[29] By comparing the performance of the Smart-Opt portfolio—which uses the information in the 70 predictors to forecast exchange rate changes—to that of the Basic-Opt portfolio—which assumes that exchange rate changes are not predictable—we can gauge the economic value of exchange rate predictability for an investor.

In addition to annualized means, volatilities, and Sharpe ratios for the portfolios, we compute the annualized average utility gain for the investor when they use the Smart-Opt in lieu of the Basic-Opt portfolio:

$$\text{Gain} = 12\big[\overline{rx}_{\text{Smart}} - 0.5\gamma\sigma^2_{\text{Smart}} - \big(\overline{rx}_{\text{Basic}} - 0.5\gamma\sigma^2_{\text{Basic}}\big)\big], \tag{37}$$

[29] We obtain similar results when we compute the portfolio excess return using simple (instead of log) currency excess returns based on the relevant forward and spot rates.

where $\overline{rx}_{\text{Smart}}$ ($\overline{rx}_{\text{Basic}}$) and σ_{Smart} (σ_{Basic}) are the mean and volatility, respectively, for the monthly Smart-Opt (Basic-Opt) portfolio excess return over the out-of-sample period. Equation (37) is the annualized increase in certainly equivalent return, which can be interpreted as the annualized portfolio management fee the investor would be willing to pay to have access to the Smart-Opt vis-à-vis the Basic-Opt portfolio.

5.2. Portfolio Performance

Table 3 reports annualized means, volatilities, and Sharpe ratios for the Smart-Opt and Basic-Opt portfolio excess returns, as well as the annualized average utility gain in Equation (37) when the investor uses the Smart-Opt instead of the Basic-Opt portfolio. In addition to the full 1995:01 to 2020:09 out-of-sample period, the table reports results for the 1995:01 to 2008:08 and 2008:09 to 2020:09 subsamples. The start of the second subsample coincides with the bankruptcy of Lehman Brothers on September 15, 2008 at the height of the global financial crisis.

Panel A of Table 3 reports performance measures for the full out-of-sample period. The Smart-Opt portfolios based on the Linear-ENet, DNN, and ensemble forecasts all perform quite well, delivering annualized Sharpe ratios between 0.90 (DNN) and 0.94 (DNN and ensemble), all of which are significant at the 1% level. The Basic-Opt portfolio, which ignores exchange rate predictability, also performs well, with an annualized Sharpe ratio of 0.66 (significant at the 1% level). Nevertheless, as evinced by the average utility gains in the second column, the Smart-Opt portfolios provide substantive economic value to the investor vis-à-vis the Basic-Opt portfolio: the investor realizes sizable annualized increases in certainty equivalent return, ranging from 330 (Linear-ENet) to 340 (ensemble) basis points.[30]

[30]For the nine countries for which we have forecasts for the full 1995:01 to 2020:09 out-of-sample period, we also compute performance measures for Smart-Opt portfolios based on the ensemble forecasts for non-US domestic investors. As shown in Table A2 of the Internet Appendix, with the exception of Switzerland, the Smart-Opt portfolio delivers substantial economic value to non-US investors, with annualized average utility gains typically well above 200 basis points.

Table 3: Portfolio Performance

The table reports portfolio performance metrics for a mean-variance US investor with a relative risk aversion coefficient of five who allocates monthly across available foreign currencies. For the Smart-Opt (Basic-Opt) portfolio, the investor uses the Linear-ENet, DNN, or ensemble (no-change) exchange rate forecasts when predicting currency excess returns. The Linear-ENet, DNN and ensemble forecasts incorporate the information in 70 predictors. The second column reports the annualized increase in certainty equivalent return when the investor uses the Smart-Opt instead of the Basic-Opt portfolio. Statistical significance for the Sharpe ratios is based on the Bao (2009) procedure; *, **, and *** indicate significance at the 10%, 5%, and 1%, levels, respectively.

(1)	(2)	(3)	(4)	(5)
Portfolio	Annualized Average Utility Gain	Annualized Mean	Annualized Volatility	Annualized Sharpe Ratio
A: 1995:01 to 2020:09 Out-of-Sample Period				
Smart-Opt, Linear-ENet	3.30%	11.52%	12.74%	0.90***
Smart-Opt, DNN	3.34%	10.75%	11.39%	0.94***
Smart-Opt, Ensemble	3.40%	11.02%	11.76%	0.94***
Basic-Opt	–	6.73%	10.14%	0.66***
B: 1995:01 to 2008:08 Out-of-Sample Period				
Smart-Opt, Linear-ENet	0.58%	13.01%	12.28%	1.06***
Smart-Opt, DNN	2.10%	13.82%	11.06%	1.25***
Smart-Opt, Ensemble	0.93%	12.63%	11.02%	1.15***
Basic-Opt	–	11.47%	10.61%	1.08***
C: 2008:09 to 2020:09 Out-of-Sample Period				
Smart-Opt, Linear-ENet	6.27%	9.83%	13.26%	0.74**
Smart-Opt, DNN	4.68%	7.27%	11.71%	0.62**
Smart-Opt, Ensemble	6.09%	9.20%	12.55%	0.73**
Basic-Opt	–	1.37%	9.39%	0.15

The results for the Basic-Opt portfolio in Panel A of Table 3 mask stark differences in the portfolio's performance over time. For the first subsample in Panel B, the average return and Sharpe ratio are considerably higher than their values for the full sample, with an annualized average return of 11.47% and Sharpe ratio of 1.08 (significant at the 1% level). As shown in Panel C, beginning in September of 2008, the average return and Sharpe ratio decline dramatically, with values of 1.37% and 0.15, respectively (the latter is insignificant at conventional levels).

In terms of the Sharpe ratio, the Smart-Opt portfolios perform fairly similarly to the Basic-Opt portfolio for the first subsample in Panel B of Table 3. The annualized Sharpe ratios for the Smart-Opt portfolios range from 1.06 (Linear-Enet) to 1.25 (DNN), all of which are significant at the 1% level. The Smart-Opt portfolios still provide additional economic value to the investor, with annualized average utility gains of 58 (Linear-ENet) to 210 (DNN) basis points. Differences in performance between the Basic-Opt and Smart-Opt portfolios become much more marked for the second subsample in Panel C. The Sharpe ratios in the last column are approximately four to five times higher for the Smart-Opt portfolios compared to those for the Basic-Opt portfolio, with values ranging from 0.62 (DNN) to 0.74 (Linear-ENet), all of which are significant at the 5% level. The annualized average utility gains accruing to the Smart-Opt portfolios are especially sizable for the second subsample, ranging from 468 (DNN) to 627 (Linear-ENet) basis points.[31]

We also construct a conventional carry trade portfolio that sorts currencies into quintiles according to interest rate differentials and then takes equally weighted long (short) positions in the currencies in the fifth (first) quintile. This is tantamount to the carry trade risk factor in Lustig, Roussanov, and Verdelhan (2011). The conventional carry portfolio generally does not perform as well as the Basic-Opt portfolio, with annualized Sharpe ratios of 0.33, 0.77, and -0.08 for the 1995 to 2020:09, 1995:01 to 2008:08, and 2008:09 to 2020:09 out-of-sample periods, respectively.[32]

[31] Providing further evidence of overfitting, when the investor uses the Linear-OLS exchange rate forecast in Equation (36), the annualized average utility gains are -1.87%, -2.48%, and -1.29% for the 1995:01 to 2020:09, 1995:01 to 2008:08, and 2008:09 to 2020:09 out-of-sample periods, respectively.

[32] The Sharpe ratio is significant at the 10% (1%) level for the full out-of-sample period (first subsample) and insignificant at conventional levels for the second subsample.

Next, we check the extent to which transaction costs affect the results. We compute portfolio excess returns using bid and ask quotes from Datastream for the relevant forward and spot rates (e.g., Lustig, Roussanov, and Verdelhan 2011). In this case, the investor is assumed to pay the bid and ask prices reported in Datastream. A number of studies document that the bid-ask spreads offered by Datastream are unrealistically high (e.g., Lyons 2001; Neely, Weller, and Ulrich 2009; Menkhoff et al. 2012b; Neely and Weller 2013). Specifically, investors trade the best quoted price at each point in time, making the full spread in Datastream considerably higher than the effective spread for FX market participants.[33] To more accurately reflect the relevant transaction costs faced by traders, we follow Goyal and Saretto (2009) and Menkhoff et al. (2012b) and also report results for currency excess returns computed using 25%, 50%, and 75% of the quoted bid-ask spreads from Datastream.

Table 4 reports portfolio performance measures adjusted for transaction costs for the 1995:01 to 2020:09 out-of-sample period. As expected, the annualized Sharpe ratios decrease monontonically as we move from Panel A (25% of the bid-ask spread) to Panel D (full bid-ask spread). Nevertheless, they remain quite sizable for the Smart-Opt portfolios: they are greater than or equal to 0.80 (0.72) for 25% (50%) of the bid-ask spread in Panel A (B); for 75% of the bid-ask spread in Panel C, they still are all 0.64.[34] The Smart-Opt portfolios also continue to provide substantive economic value to the investor vis-à-vis the Basic-Opt portfolio in terms of the annualized average utility gains in the second column. Even for 75% of the bid-ask spread, the gains are all above 300 basis points. In sum, the performance of the Smart-Opt portfolio—and thus the economic value of out-of-sample exchange rate predictability—is robust to reasonable assumptions regarding transaction costs.

[33] The FX market is one of the most liquid markets, with low transaction costs and no natural short-selling constraints. According to the 2016 Bank for International Settlements Triennial Survey, average daily turnover in the FX market is five trillion US dollars.

[34] All of the Sharpe ratios for the Smart-Opt portfolios are significant at the 1% level in Panels A through C of Table 4.

Table 4: Portfolio Performance with Transaction Costs

The table reports portfolio performance metrics for a mean-variance US investor with a relative risk aversion coefficient of five who allocates monthly across available foreign currencies for the 1995:01 to 2020:09 out-of-sample period. Results are reported for different assumptions regarding transaction costs for bid-ask spreads from Datastream. For the Smart-Opt (Basic-Opt) portfolio, the investor uses the Linear-ENet, DNN, or ensemble (no-change) exchange rate forecasts when predicting currency excess returns. The Linear-ENet, DNN, and ensemble exchange rate forecasts incorporate the information in 70 predictors. The second column reports the annualized increase in certainty equivalent return when the investor uses the Smart-Opt instead of the Basic-Opt portfolio. Statistical significance for the Sharpe ratios is based on the Bao (2009) procedure; *, **, and *** indicate significance at the 10%, 5%, and 1%, levels, respectively.

(1) Portfolio	(2) Annualized Average Utility Gain	(3) Annualized Mean	(4) Annualized Volatility	(5) Annualized Sharpe Ratio
		A: 25% of Bid-Ask Spread		
Smart-Opt, Linear-ENet	3.19%	10.40%	12.98%	0.80***
Smart-Opt, DNN	3.17%	9.51%	11.56%	0.82***
Smart-Opt, Ensemble	3.22%	9.80%	11.98%	0.82***
Basic-Opt	–	5.59%	10.18%	0.55***
		B: 50% of Bid-Ask Spread		
Smart-Opt, Linear-ENet	3.11%	9.34%	12.98%	0.72***
Smart-Opt, DNN	3.11%	8.47%	11.55%	0.73***
Smart-Opt, Ensemble	3.14%	8.74%	11.97%	0.73***
Basic-Opt	–	4.61%	10.17%	0.45**
		C: 75% of Bid-Ask Spread		
Smart-Opt, Linear-ENet	3.03%	8.28%	12.97%	0.64***
Smart-Opt, DNN	3.06%	7.43%	11.53%	0.64***
Smart-Opt, Ensemble	3.06%	7.68%	11.96%	0.64***
Basic-Opt	–	3.63%	10.16%	0.36*
		D: Full Bid-Ask Spread		
Smart-Opt, Linear-ENet	2.95%	7.21%	12.96%	0.56***
Smart-Opt, DNN	3.00%	6.39%	11.52%	0.55**
Smart-Opt, Ensemble	2.98%	6.61%	11.95%	0.55***
Basic-Opt	–	2.64%	10.15%	0.26

To provide additional perspective on relative performance, Figure 7 depicts log cumulative excess returns for the Smart-Opt portfolio based on the ensemble forecasts, as well as the Basic-Opt and conventional carry trade portfolios.[35] The Smart-Opt and Basic-Opt portfolios perform somewhat similarly through the summer of 2008, although the Smart-Opt portfolio fares substantially better in the late 1990s and early 2000s in the wake of the Asian financial and Long-Term Capital Management crises. While both portfolios experience losses in September of 2008 during the Lehman bankruptcy, their subsequent performances differ markedly, in line with Panel C of Table 3. The Basic-Opt portfolio suffers more sizable losses later in 2008 in Figure 7, and its cumulative return essentially "flatlines" thereafter. The conventional carry portfolio, which is not based on an optimization framework, suffers an even larger drop in late 2008 compared to the Basic-Opt portfolio and also flatlines subsequently. In sharp contrast, the Smart-Opt portfolio makes a strong recovery in late 2008 and continues to produce gains on a consistent basis thereafter.[36]

The relatively strong performance of the Smart-Opt portfolio in late 2008 in Figure 7 aligns with the large out-of-sample gains accruing to the ensemble forecasts vis-à-vis the no-change benchmark during that time in Figure 4. The Basic-Opt portfolio simply uses the bill yield differential to forecast the currency excess return in Equation (36)—in line with the no-change benchmark forecast—while the Smart-Opt portfolio incorporates the information in the predictors via the ensemble forecast. The accuracy gains generated by the ensemble forecasts relative to the no-change benchmark in late 2008 and beyond in Figure 4 translate into economic gains in the form of improved portfolio performance in Figure 7.

Further evidence on the links between exchange rate predictability and the carry portfolios is furnished by Figure 8, which portrays the currency weights for the Smart-Opt portfolio

[35] The result are qualitatively similar for the Basic-Opt portfolios based on the Linear-ENet and DNN forecasts.

[36] It is interesting to note that the Smart-Opt portfolio also performs considerably better than the Basic-Opt and conventional carry trade portfolios in Figure 7 near the advent of the COVID-19 crisis in early 2020 through the end of the out-of-sample period.

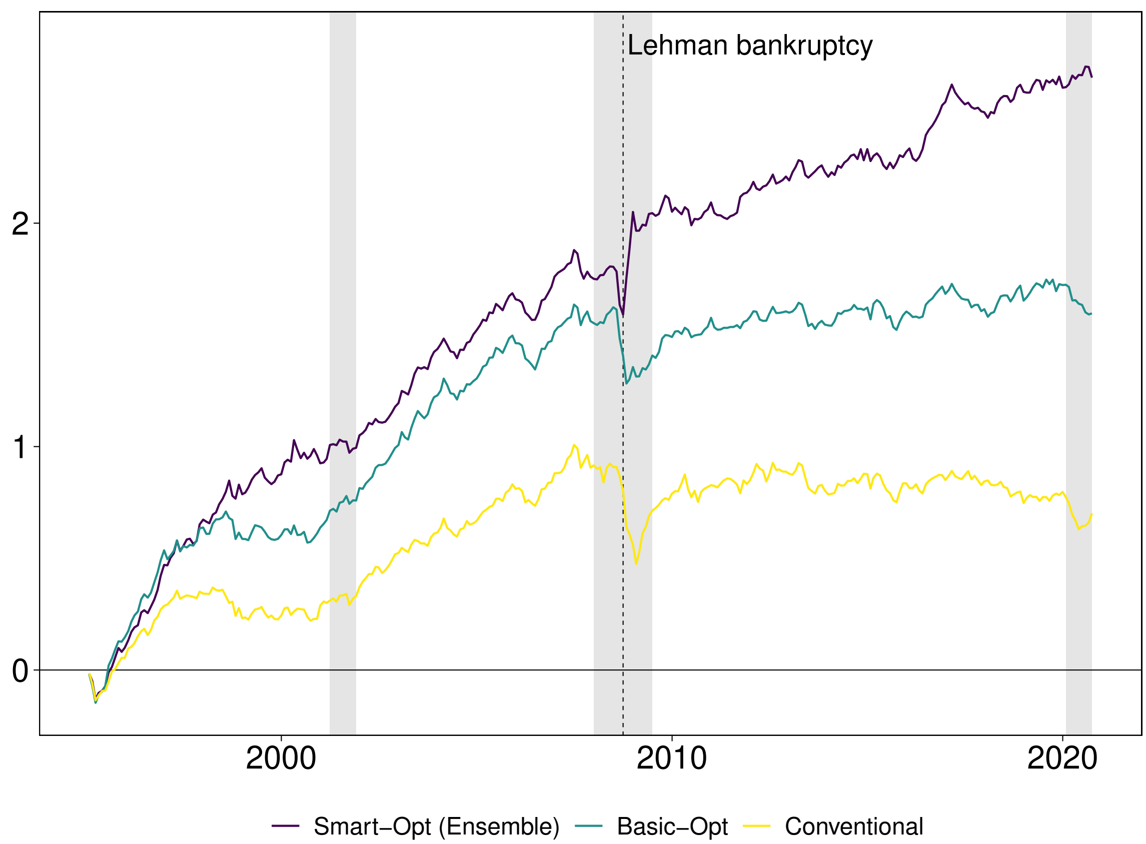


Figure 7. Log cumulative portfolio excess returns. The figure depicts log cumulative excess returns for the Basic-Opt portfolio based on the ensemble forecasts, Basic-Opt portfolio, and a conventional carry trade portfolio. Vertical bars delineate business-cycle recessions as dated by the National Bureau of Economic Research.

based on the ensemble forecasts and the Basic-Opt portfolio. As the figure illustrates, by incorporating information from the predictors, the ensemble forecasts often lead to substantially different allocations. The differences in allocations produced by the ensemble forecasts vis-à-vis the no-change benchmark in Equation (34) deliver improved carry trade portfolio performance in Table 3 and Figure 7.

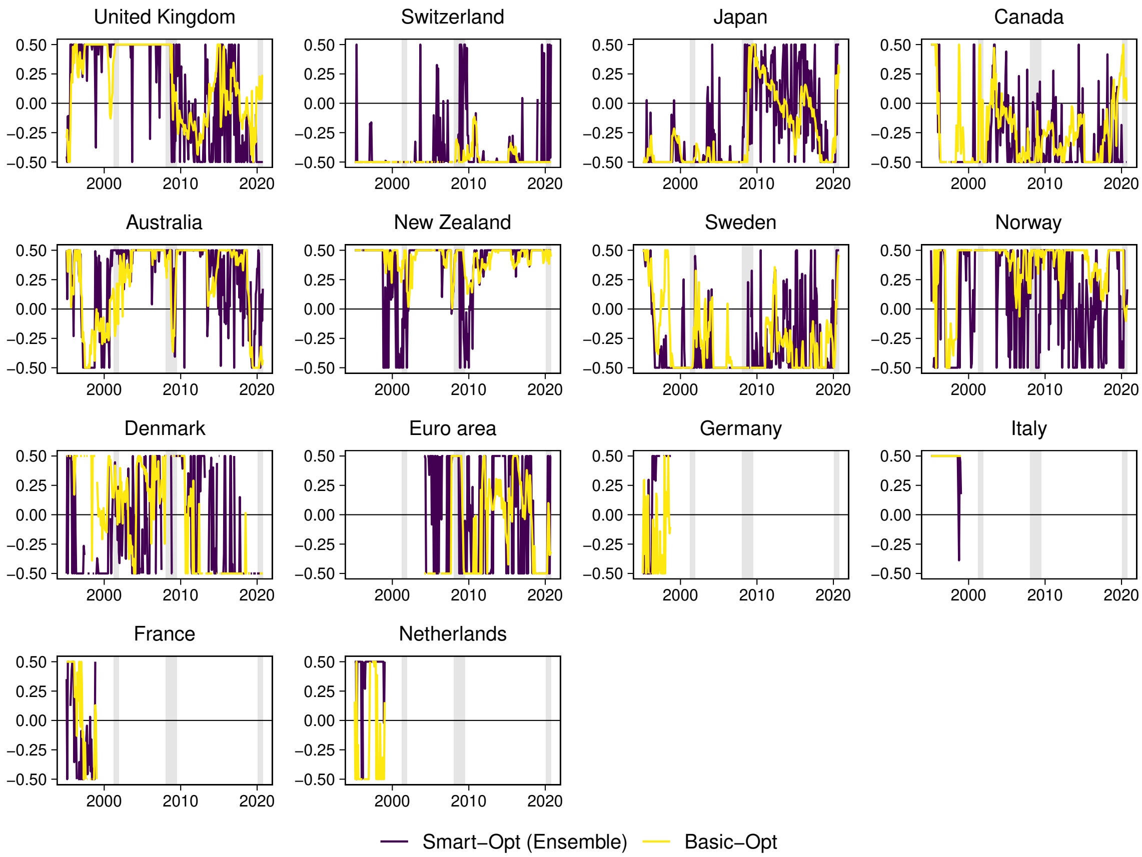


Figure 8. Portfolio weights. The figure depicts allocations to foreign currencies for the Smart-Opt and Basic-Opt portfolios. The Smart-Opt portfolio is based on the ensemble forecasts. Vertical bars delineate business-cycle recessions as dated by the National Bureau of Economic Research.

5.3. A Closer Look at Late 2008

Figure 7 indicates that late 2008 is a perilous time for the Basic-Opt portfolio (as well as the conventional carry portfolio). Figures 9 and 10 provide additional insight into the sources of the poor performance of the Basic-Opt portfolio in late 2008, as well as how the Smart-Opt portfolio (based on the ensemble forecasts) improves performance. Figure 9 shows the currency excess return forecasts that serve as inputs in the portfolio optimization problem in Equation (34), along with the realized excess returns, for September through

December of 2008. Because the Basic-Opt portfolio uses the no-change benchmark exchange rate forecast, the benchmark currency excess return forecast in Equation (36) is simply the bill yield differential; the Smart-Opt portfolio augments the bill yield differential with the ensemble forecast of the exchange rate change. Figure 10 displays the currency weights for the portfolios.

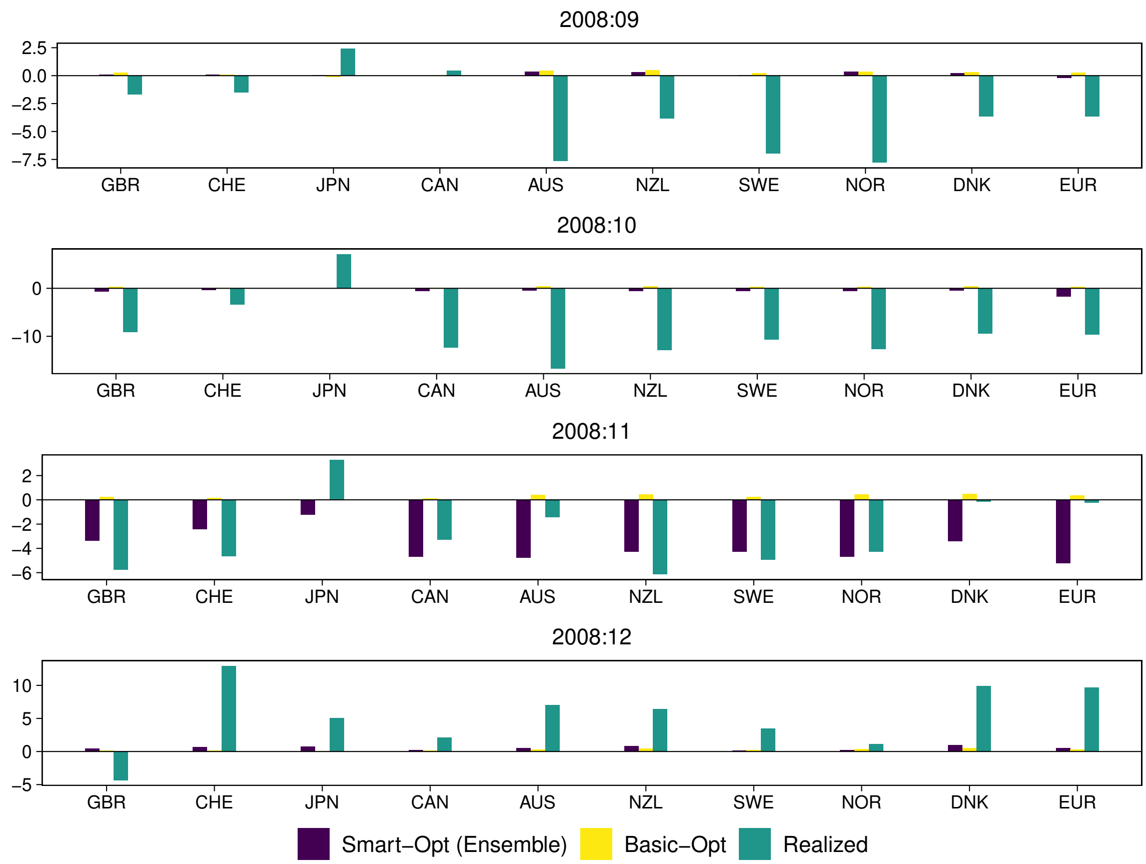


Figure 9. Currency excess returns forecasts. The figure depicts currency excess return forecasts that serve as inputs for the Smart-Opt and Basic-Opt portfolios for the final four months of 2008. The Smart-Opt portfolio is based on the ensemble forecasts. The figure also depicts realized values for the currency excess returns.

For September of 2008, the ensemble and benchmark currency excess return forecasts in Figure 9 lead to allocations of the same signs (and typically similar magnitudes) in Figure 10 for Switzerland, Canada, Australia, New Zealand, Sweden, Norway, and Denmark. The ensemble currency excess return forecasts generate notable differences in allocations for the other countries: for the United Kingdom and Euro area, the Smart-Opt (Basic-Opt) portfolio takes short (long) positions; for Japan, the Smart-Opt (Basic-Opt) portfolio takes a long (short) position. As shown in Figure 9, with the exceptions of Japan and Canada, all of the realized currency excess returns are negative for September of 2008; the negative returns are large in magnitude for Australia, New Zealand, Sweden, Norway, Denmark, and the Euro area. On the basis of the allocations and realized currency excess returns, the excess return for the Basic-Opt portfolio is −7.57% in September of 2008, while the loss is smaller (−4.24%) for the Smart-Opt portfolio. The differences in allocations signaled by the ensemble forecasts—especially for the United Kingdom, Japan, and Euro area—help to limit portfolio losses in the month of the Lehman bankruptcy.

The currency excess return forecasts diverge more sharply during October of 2008 in Figure 9: with the exception of Japan, the benchmark currency excess return forecasts are all positive, while the ensemble forecasts are negative for all ten of the countries. The differences in currency excess return forecasts give rise to a number of markedly different allocations during October of 2008 in Figure 10; most notably, the Smart-Opt (Basic-Opt) portfolio exhibits sizable short (long) positions for the United Kingdom, New Zealand, Norway, Denmark, and Euro area. With the exception of Japan, all of the realized currency excess returns are negative for October of 2008 in Figure 9, and the negative returns are larger in magnitude than those for September of 2008.[37] The different allocations prompted by the ensemble forecasts vis-à-vis the no-change benchmark enable the Smart-Opt portfolio to substantively outperform the Basic-Opt portfolio during October of 2008: the latter suffers a large loss of −11.60%, while the former enjoys a substantial gain of 17.74%. The situation for November of 2008 is fairly similar to that for October in terms of the currency excess return forecasts and allocations in Figures 9 and 10. Because the negative realized currency excess returns are typically smaller in magnitude, the Basic-Opt realizes an excess return of 1.91% during

[37]Note the difference in scales for the vertical axes across the top two panels of Figure 9.

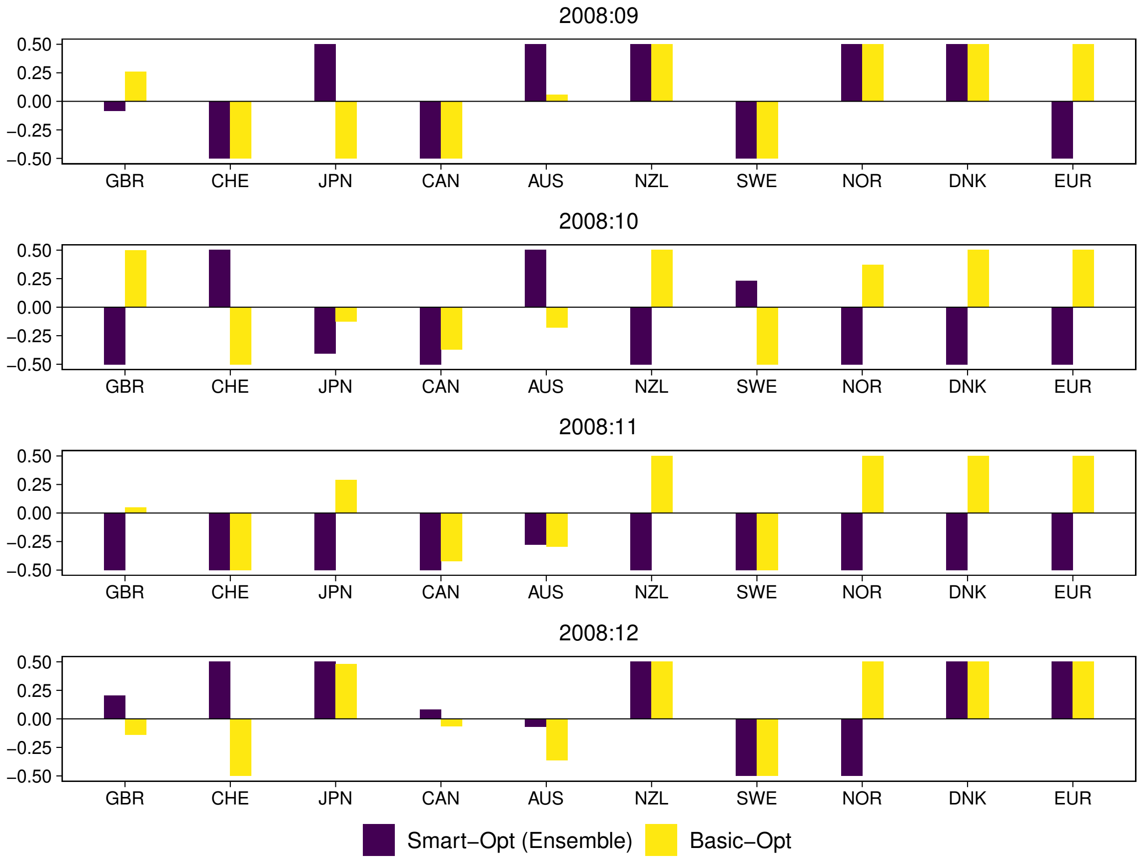


Figure 10. Portfolio weights for late 2008. The figure depicts allocations to foreign currencies for the Smart-Opt and Basic-Opt portfolios for the final four months of 2008. The Smart-Opt portfolio is based on the ensemble forecasts.

the month; however, the information in the ensemble forecasts leads to a much larger excess return of 13.46% for the Smart-Opt portfolio.

The environment appears to normalize to an extent in December of 2008, in the sense that the discrepancies between the ensemble and benchmark forecasts in Figure 9, as well as those between the Smart-Opt and Basic-Opt portfolio weights in Figure 10, are more muted. Nevertheless, important differences remain (e.g., the portfolio weights for Switzerland and Norway). In addition, with the exception of the United Kingdom, all of the realized currency excess returns are positive in December of 2008. The Basic-Opt portfolio experiences an excess return of 5.64% for the month, while it is more than three times as large (18.48%) for the Smart-Opt portfolio.[38]

Figures 9 and 10 help to explain how exchange rate predictability—as captured by the ensemble forecasts—is especially valuable to an investor during the worst part of the global financial crisis in late 2008. By anticipating depreciations in many foreign currencies, the ensemble forecasts lead to sizable negative positions in many currencies, enabling the Smart-Opt portfolio to avoid the large losses suffered by a basic carry strategy and even realize large gains. In essence, the Smart-Opt portfolio shorts the traditional carry strategy to a significant extent during the tumult of the global financial crisis.

5.4. Alphas

Finally, we examine whether the Smart-Opt and Basic-Opt portfolios generate alpha in the context of the Lustig, Roussanov, and Verdelhan (2011) currency factor model. The model includes dollar and carry trade risk factors, denoted by $\mathrm{MKT}_{\mathrm{FX}}$ and $\mathrm{HML}_{\mathrm{FX}}$, respectively. The dollar factor is an equally weighted average of the available currency excess returns for the month, while the carry trade risk factor is the conventional carry portfolio defined previously. Table 5 reports factor model estimation results for the Basic-Opt and Smart-Opt portfolios. We again report results for the full out-of-sample period, as well as the 1995:01 to 2008:08 and 2008:09 to 2020:09 subsamples.

For the full 1995:01 to 2020:09 out-of-sample period in Panel A of Table 5, the Smart-Opt portfolios generate large annualized alphas of 9.92%, 9.53%, and 9.61% for the Linear-ENet, DNN, and ensemble forecasts, respectively, all of which are significant at the 1% level and substantially larger than that for the Basic-Opt portfolio (4.27%). The Basic-Opt portfolio evinces considerable exposure to the carry factor (0.77, significant at the 1% level) for the full

[38] For September through December of 2008, the excess returns for the conventional carry trade portfolio are −6.33%, −15.00%, −3.06%, and −4.77%, respectively, in line with the sharp drop in the portfolio's cumulative excess return in Figure 7.

Table 5: Alphas

The table reports Lustig, Roussanov, and Verdelhan (2011) factor model estimation results for the Smart-Opt portfolio based on the Linear-ENet, DNN, and ensemble forecasts, as well as the Basic-Opt portfolio. For the Smart-Opt (Basic-Opt) portfolio, a mean-variance US investor with a relative risk aversion coefficient of five allocates monthly across available foreign currencies using the Linear-ENet, DNN, or ensemble (no-change) exchange rate forecasts when predicting currency excess returns. The Linear-ENet, DNN and ensemble exchange rate forecasts incorporate the information in 70 predictors. For the second through fourth columns, *, **, and *** indicate significance at the 10%, 5%, and 1%, levels, respectively.

(1)	(2)	(3)	(4)	(6)
Portfolio	Annualized Alpha	MKT_{FX}	HML_{FX}	Adjusted R^2
A: 1995:01 to 2020:09 Out-of-Sample Period				
Smart-Opt, Linear-ENet	9.92%***	-0.56^{***}	0.47^{**}	16.97%
Smart-Opt, DNN	9.53%***	-0.05	0.38^{***}	9.18%
Smart-Opt, Ensemble	9.61%***	-0.29^{**}	0.42^{**}	11.58%
Basic-Opt	4.27%***	-0.03	0.77^{***}	52.89%
B: 1995:01 to 2008:08 Out-of-Sample Period				
Smart-Opt, Linear-ENet	7.63%***	-0.47^{**}	0.87^{***}	46.07%
Smart-Opt, DNN	9.12%***	0.08	0.69^{***}	29.12%
Smart-Opt, Ensemble	7.48%***	-0.22	0.79^{***}	41.81%
Basic-Opt	4.85%***	0.18^{**}	0.95^{***}	63.62%
C: 2008:09 to 2020:09 Out-of-Sample Period				
Smart-Opt, Linear-ENet	9.33%**	-0.37^{**}	0.07	3.29%
Smart-Opt, DNN	7.38%**	0.02	0.09	-0.54%
Smart-Opt, Ensemble	9.08%**	-0.11	0.06	-0.98%
Basic-Opt	1.71%	-0.12	0.64^{***}	45.26%

out-of-sample period. The Smart-Opt portfolios also exhibit sizable exposures to the carry factor (0.47, 0.38, and 0.42 for the Linear-ENet, DNN, and ensemble forecasts, respectively, all of which are significant at the 5% or 1% level), but they are about half as large as that for the Basic-Opt portfolio.

Panels B and C of Table 5 reveal important differences in performance for the Basic-Opt portfolio across the two subsamples. For the 1995:01 to 2008:08 subsample in Panel B, the Basic-Opt portfolio exhibits near unitary exposure to the carry trade factor (0.95, significant at the 1% level), and it generates a sizable annualized alpha of 4.85% (significant at the 1% level). Reminiscent of Table 3 and Figure 7, the Basic-Opt portfolio's performance deteriorates sharply for the 2008:09 to 2020:09 subsample in Panel C. It continues to display substantial exposure to the carry factor (0.64, significant at the 1% level), while its annualized alpha declines to only 1.71% (insignificant at conventional levels). In contrast, the Smart-Opt portfolios deliver impressive annualized alphas for both subsamples in Panels B and C of Table 5, all of which are well above 700 basis points and significant at the 5% or 1% level. An interesting pattern emerges with respect to the exposures of the Smart-Opt portfolios to the carry factor. The exposures are quite sizable for the first subsample, ranging from 0.69 (DNN) to 0.87 (Linear-ENet), and all are significant at the 1% level. For the second subsample, the exposures become close to zero, and none are significant at conventional levels. The information contained in the 70 predictors thus leads the investor to effectively disconnect fully from a conventional carry strategy in the second subsample.

6. Conclusion

Short-horizon exchange rate prediction has posed an enduring challenge to researchers in international finance. In this paper, we make considerable progress in resolving the Meese and Rogoff (1983) no-predictability puzzle by showing that out-of-sample forecasts of monthly US dollar exchange rates can significantly outperform the no-change benchmark over a lengthy out-of-sample period for a group of developed countries. Our forecasting approach has two key elements. First, we consider a rich information set, which includes ten country characteristics and six global variables; after interacting the country characteristics with the global variables, we have 70 predictors for our panel predictive regressions. It is important to consider a large number of potential predictors, rather than only a few fundamentals, as we cannot know a priori which predictors are the most relevant. Second, we employ machine learning techniques, including ENet estimation of linear models, which uses penalized regression to alleviate overfitting in our high-dimensional and noisy data setting, and DNNs, which allow for complex nonlinear predictive relationships.

For out-of-sample exchange rate prediction, it is important to move beyond off-the-shelf implementations of machine learning techniques. Monthly exchange rate fluctuations inherently contain a large unpredictable component—which means we are dealing with very noisy data when training models—so that we need to take additional steps to better guard against overfitting. With respect to fitting linear panel predictive regressions via the ENet, we use the ERIC to tune the shrinkage hyperparameter λ. Relative to conventional cross validation, the ERIC tends to select a larger value of λ and thus induces greater shrinkage, which better guards against overfitting in our high-dimensional and noisy data environment. We also set the intercept terms in the linear panel predictive regressions to zero, which imposes the economic restrictions that the mean exchange rate changes are zero. These restrictions are consistent with the data and reduce the number of parameters we need to estimate, further helping to guard against overfitting. For the DNNs, we set the intercept terms for the weights to zero, which is analogous to setting the intercept terms in the linear panel predictive regressions to zero. This again helps to alleviate overfitting by reducing the number of parameters we need to estimate, which is particularly useful given the large number of weights in DNNs. To further guard against overfitting when training the DNNs, we include ℓ_1 and ℓ_2 penalty terms in the objective function and employ dropout. We also consider an ensemble forecast that takes the average of the Linear-ENet and DNN forecasts. We find that the ensemble forecast exhibits the best overall performance. Furthermore, we interpret the fitted models underlying the forecasts by assessing the importance of individual predictors via the recently developed approach of Greenwell, Boehmke, and McCarthy (2018). We find that inflation and bill yield differentials—two of the most popular fundamentals in the literature—are among the most relevant predictors, once they interact with global FX volatility.

In addition to improving out-of-sample prediction in terms of MSPE, we show that exchange rate forecasts based on machine learning provide substantive economic value to a US investor. Specifically, the performance of an optimal portfolio for a mean-variance investor who allocates across foreign currencies improves markedly when the investor utilizes machine learning forecasts of exchange rate changes for predicting currency excess returns. The machine learning forecasts are especially valuable to the investor during and after the global financial crisis. During the worst phase of the crisis in late 2008, the machine learning forecasts generate substantial improvements in portfolio performance by anticipating sharp devaluations in many foreign currencies, consistent with heightened uncertainty and the US dollar's safe-haven role.

Our fresh evidence of out-of-sample exchange range predictability raises fundamental issues in international finance. What are the theoretical underpinnings of exchange rate predictability? To what extent does predictability reflect rational time-varying risk premia and/or mispricing in the FX market? Do arbitrage frictions play a significant role, even though transactions costs are relatively small in major currency markets? In light of our new evidence, we view these questions as important topics for future research.

References

Adrian, T. and P. Xie (2020). The Non-U.S. Bank Demand for U.S. Dollar Assets. IMF Working Paper No. 20/101.

Ang, A. and J. Chen (2011). Yield Curve Predictors of Foreign Exchange Returns. Working Paper.

Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring Economic Policy Uncertainty. *Quarterly Journal of Economics* 131, 1593–1636.

Bakshi, G. and G. Panayotov (2013). Predictability of Currency Carry Trades and Asset Pricing Implications. *Journal of Financial Economics* 110, 139–163.

Bao, Y. (2009). Estimation Risk-Adjusted Sharpe Ratio and Fund Performance Ranking under a General Return Distribution. *Journal of Financial Econometrics* 7, 152–173.

Barron, A. R. (1994). Approximation and Estimation Bounds for Artificial Neural Networks. *Machine Learning* 14, 115–133.

Bickel, P. J., Y. Ritov, and A. B. Tsybakov (2009). Simultaneous Analysis of Lasso and Dantzig Selector. *Annals of Statistics* 37, 1705–1732.

Bilson, J. F. O. (1981). The "Speculative Efficiency" Hypothesis. *Journal of Business* 54, 435–451.

Brunnermeier, M. K., S. Nagel, and L. H. Pedersen (2009). Carry Trades and Currency Crashes. In: D. Acemoglu, K. Rogoff, and M. Woodford, eds. *NBER Macroeconomics Annual 2008*. Vol. 23. Chicago: University of Chicago Press, pp. 313–347.

Burnside, C. (2018). Exchange Rates, Interest Parity, and the Carry Trade. Working Paper.

Burnside, C., M. Eichenbaum, I. Kleshchelski, and S. Rebelo (2011). Do Peso Problems Explain the Returns to the Carry Trade? *Review of Financial Studies* 24, 853–891.

Burnside, C., M. Eichenbaum, and S. Rebelo (2011). Carry Trade and Momentum in Currency Markets. *Annual Review of Finance and Economics* 3, 511–535.

Caldara, D. and M. Iacoviello (2018). Measuring Geopolitical Risk. Federal Reserve Board of Governors International Finance Discussion Paper No. 1222.

Campbell, J. Y. and S. B. Thompson (2008). Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average? *Review of Financial Studies* 21, 1509–1531.

Cenedese, G., R. Payne, L. Sarno, and G. Valente (2016). What Do Stock Markets Tell Us About Exchange Rates? *Review of Finance* 20, 1045–1080.

Chen, Y.-C. and K. P. Tsang (2013). What Does the Yield Curve Tell Us About Exchange Rate Predictability? *Review of Economics and Statistics* 95, 185–205.

Chen, L., M. Pelger, and J. Zhu (2020). Deep Learning in Asset Pricing. Working Paper.

Chinco, A., A. D. Clark-Joseph, and M. Ye (2019). Sparse Signals in the Cross-Section of Returns. *Journal of Finance* 74, 449–492.

Christiano, L. J. and T. J. Fitzgerald (2003). The Band Pass Filter. *International Economic Review* 44, 435–465.

Clark, T. E. and M. W. McCracken (2001). Tests of Equal Forecast Accuracy and Ecompassing for Nested Models. *Journal of Econometrics* 105, 85–110.

Clark, T. E. and K. D. West (2007). Approximately Normal Tests for Equal Predictive Accuracy in Nested Models. *Journal of Econometrics* 138, 291–311.

Cybenko, G. (1989). Approximation by Superpositions of a Sigmoidal Function. *Mathematics of Control, Signals, and Systems* 2, 303–314.

Dahlquist, M. and H. Hasseltoft (2020). Economic Momentum and Currency Returns. *Journal of Financial Economics* 136, 152–167.

Daniel, K., R. J. Hodrick, and Z. Lu (2017). The Carry Trade: Risks and Drawdowns. *Critical Finance Review* 6, 211–262.

Della Corte, P., A. Jeanneret, and E. Patelli (2020). A Credit-Based Theory of the Currency Risk Premium. Working Paper.

Della Corte, P., L. Sarno, and I. Tsiakas (2009). An Economic Evaluation of Empirical Exchange Rate Models. *Review of Financial Studies* 22, 3491–3530.

Diebold, F. X. and R. S. Mariano (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics* 13, 253–263.

Dobrynskaya, V. (2014). Downside Market Risk of Carry Trades. *Review of Finance* 18, 1885–1913.

Dong, X., Y. Li, D. E. Rapach, and G. Zhou (forthcoming). Anomalies and the Expected Market Return. *Journal of Finance*.

Engel, C. and K. D. West (2005). Exchange Rates and Fundamentals. *Journal of Political Economy* 113, 485–517.

Engel, C. and S. P. Y. Wu (2019). Liquidity and Exchange Rates: An Empirical Investigation. NBER Working Paper No. 25397.

Fama, E. F. (1984). Forward and Spot Exchange Rates. *Journal of Monetary Economics* 14, 319–338.

Filippou, I. and M. P. Taylor (2017). Common Macro Factors and Currency Premia. *Journal of Financial and Quantitative Analysis* 52, 1731–1763.

Frenkel, J. A. (1976). A Monetary Approach to the Exchange Rate: Doctrinal Aspects and Empirical Evidence. *Scandinavian Journal of Economics* 78, 200–224.

Freyberger, J., A. Neuhierl, and M. Weber (2020). Dissecting Characteristics Nonparametrically. *Review of Financial Studies* 33, 2326–2377.

Friedman, J. H. (2001). Greedy Function Approximation: A Gradient Boosting Machine. *Annals of Statistics* 29, 1189–1232.

Froot, K. A. and R. H. Thaler (1990). Anomalies: Foreign Exchange. *Journal of Economic Perspectives* 4, 179–192.

Funahashi, K.-I. (1989). On the Approximate Realization of Continuous Mappings by Neural Networks. *Neural Networks* 2, 183–192.

Goodfellow, I., Y. Bengio, and A. Courville (2016). *Deep Learning*. Cambridge, MA: MIT Press.

Goyal, A. and A. Saretto (2009). Cross-Section of Option Returns and Volatility. *Journal of Financial Economics* 94, 310–326.

Goyal, A. and I. Welch (2003). Predicting the Equity Premium with Dividend Ratios. *Management Science* 49, 639–654.

Goyal, A. and I. Welch (2008). A Comprehensive Look at the Empirical Performance of Equity Premium Prediction. *Review of Financial Studies* 21, 1455–1508.

Greenwell, B. M., B. C. Boehmke, and A. J. McCarthy (2018). A Simple and Effective Model-Based Variable Importance Measure. Working Paper (arXiv:1805.04755v1).

Gu, S., B. Kelly, and D. Xiu (2020). Empirical Asset Pricing via Machine Learning. *Review of Financial Studies* 33, 2223–2273.

Han, Y., A. He, D. E. Rapach, and G. Zhou (2021). Cross-Sectional Out-of-Sample Stock Return Prediction with Many Characteristics. Working Paper.

Hansen, L. P. and R. J. Hodrick (1980). Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis. *Journal of Political Economy* 88, 829–853.

Hastie, T. and J. Qian (2016). Glmnet Vignette. Working Paper.

Hau, H. and H. Rey (2006). Exchange Rates, Equity Prices, and Capital Flows. *Review of Financial Studies* 19, 273–317.

Hinton, G. E., N. Srivastava, A. Krizhevsky, I. Sutskever, and R. R. Salakhutdinov (2012). Improving Neural Networks by Preventing Co-Adaptation of Feature Detectors. Working Paper (arXiv:1207.0580).

Hodrick, R. J. and E. C. Prescott (1997). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit, and Banking* 19, 1–16.

Hoerl, A. E. and R. W. Kennard (1970). Ridge Regression: Applications to Nonorthogonal Problems. *Technometrics* 12, 69–82.

Hornik, K. (1991). Approximation Capabilities of Multilayer Feedforward Networks. *Neural Networks* 4, 251–257.

Hornik, K., M. Stinchcombe, and H. White (1989). Multilayer Feedforward Networks Are Universal Approximators. *Neural Networks* 2, 359–366.

Hui, F. K. C., D. I. Warton, and S. D. Foster (2015). Tuning Parameter Selection for the Adaptive Lasso Using ERIC. *Journal of the American Statistical Society* 110, 262–269.

Jiang, Z., A. Krishnamurthy, and H. Lustig (2021). Foreign Safe Asset Demand and the Dollar Exchange Rate. *Journal of Finance* 76, 1049–1089.

Jordà, Ò. and A. M. Taylor (2012). The Carry Trade and Fundamentals: Nothing to Fear but FEER Itself. *Journal of International Economics* 88, 74–90.

Jurek, J. W. (2014). Crash-Neutral Currency Carry Trades. *Journal of Financial Economics* 113, 325–347.

Kilian, L. and M. P. Taylor (2003). Why Is It So Difficult to Beat the Random Walk Forecast of Exchange Rates? *Journal of International Economics* 60, 85–107.

Kingma, D. P. and J. Ba (2015). Adam: A Method for Stochastic Optimization. In: *Third Annual International Conference on Learning Representations.*

Kozak, S., S. Nagel, and S. Santosh (2020). Shrinking the Cross Section. *Journal of Financial Economics* 135, 271–292.

Kremens, L. and I. Martin (2019). The Quanto Theory of Exchange Rates. *American Economic Review* 109, 810–843.

Lettau, M., M. Maggiori, and M. Weber (2014). Conditional Risk Premia in Currency Markets and Other Asset Classes. *Journal of Financial Economics* 114, 197–225.

Lilley, A., M. Maggiori, B. Neiman, and J. Schreger (forthcoming). Exchange Rate Reconnect. *Review of Economics and Statistics.*

Lundberg, S. M. and S.-I. Lee (2017). A Unified Approach to Interpreting Model Predictions. In: *Proceedings of the 31st International Conference on Neural Information Processing Systems.*

Lustig, H., N. Roussanov, and A. Verdelhan (2011). Common Risk Factors in Currency Markets. *Review of Financial Studies* 24, 3731–3777.

Lyons, R. K. (2001). *The Microstructure Approach to Exchange Rates.* Cambridge, MA: MIT Press.

Maas, A. L., A. Y. Hannun, and A. Y. Ng (2013). Rectifier Nonlinearities Improve Neural Network Acoustic Models. In: *Proceedings of the 30th International Conference on Machine Learning.*

McCracken, M. W. (2007). Asymptotics for Out of Sample Tests of Granger Causality. *Journal of Econometrics* 140, 719–752.

Meese, R. A. and K. Rogoff (1983). Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample? *Journal of International Economics* 14, 3–24.

Meinshausen, N. and B. Yu (2009). Lasso-Type Recovery of Sparse Representations for High-Dimensional Data. *Annals of Statistics* 37, 246–270.

Melvin, M. and D. Shand (2017). When Carry Goes Bad: The Magnitude, Causes, and Duration of Currency Carry Unwinds. *Financial Analysts Journal* 73, 121–144.

Melvin, M. and M. P. Taylor (2009). The Crisis in the Foreign Exchange Market. *Journal of International Money and Finance* 28, 1317–1330.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012a). Carry Trades and Global Foreign Exchange Volatility. *Journal of Finance* 67, 681–718.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012b). Currency Momentum Strategies. *Journal of Financial Economics* 106, 660–684.

Molodtsova, T. and D. H. Papell (2009). Out-of-Sample Exchange Rate Predictability with Taylor Rule Fundamentals. *Journal of International Economics* 77, 167–180.

Mueller, P., A. Stathopoulos, and A. Vedolin (2017). International Correlation Risk. *Journal of Financial Economics* 126, 270–299.

Mussa, M. (1976). The Exchange Rate, the Balance of Payments and Monetary and Fiscal Policy under a Regime of Controlled Floating. *Scandinavian Journal of Economics* 78, 229–248.

Nagel, S. (2021). *Machine Learning in Asset Pricing*. Princeton: Princeton University Press.

Neely, C. J. and P. A. Weller (2013). Lessons from the Evolution of Foreign Exchange Trading Strategies. *Journal of Banking and Finance* 37, 3783–3798.

Neely, C. J., P. A. Weller, and J. M. Ulrich (2009). The Adaptive Markets Hypothesis: Evidence from the Foreign Exchange Market. *Journal of Financial and Quantitative Analysis* 44, 467–488.

Rapach, D. E., J. K. Strauss, and G. Zhou (2013). International Stock Return Predictability: What Is the Role of the United States? *Journal of Finance* 68, 1633–1662.

Rapach, D. E. and G. Zhou (2013). Forecasting Stock Returns. In: G. Elliott and A. Timmermann, eds. *Handbook of Economic Forecasting*. Vol. 2A. Amsterdam: Elsevier, pp. 328–383.

Rolnick, D. and M. Tegmark (2018). The Power of Deeper Networks for Expressing Natural Functions. In: *Sixth Annual International Conference on Learning Representations*.

Rossi, B. (2013). Exchange Rate Predictability. *Journal of Economic Literature* 51, 1063–1119.

Schwarz, G. (1978). Estimating the Dimension of a Model. *Annals of Statistics* 6, 461–464.

Srivastava, N., G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov (2014). Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *Journal of Machine Learning Research* 15, 1929–1958.

Taylor, J. B. (1993). Discretion Versus Policy Rules in Practice. *Carnegie-Rochester Conference Series on Public Policy* 39, 195–214.

Taylor, M. P. (1995). The Economics of Exchange Rates. *Journal of Economic Literature* 33, 13–47.

Tibshirani, R. (1996). Regression Shrinkage and Selection via the LASSO. *Journal of the Royal Statistical Society. Series B (Methodological)* 58, 267–288.

West, K. D. (1996). Asymptotic Inference about Predictive Ability. *Econometrica* 64, 1067–1084.

Zhang, C.-H. and J. Huang (2008). The Sparsity and Bias of the Lasso Selection in High-Dimensional Linear Regression. *Annals of Statistics* 36, 1567–1594.

Zou, H. and T. Hastie (2005). Regularization and Variable Selection via the Elastic Net. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)* 67, 301–320.