Internet Appendix for
"Exchange Rate Prediction with Machine Learning and a Smart Carry Trade Portfolio"

Not for Publication

January 25, 2022

A1. Data

This section provides details on the data sources and construction of the country characteristics and global variables.

A1.1. Exchange Rates

Daily bid and ask spot and forward exchange rates are from Barclays and Reuters via Datastream. Datastream country mnemonics for currencies are as follows: United Kingdom, GBP; Switzerland, CHF; Japan, JPY; Canada, CAD; Australia, AUD; New Zealand, NZD; Sweden, SEK; Norway, NOK; Denmark, DKK; Euro area, EUR; Germany, DEM; Italy, ITL; France, FRF; Netherlands, NLG.

Bid spot price Ticker BB***SP(EB), where "***" indicates the country mnemonic.

Ask spot price Ticker BB***SP(EO).

Bid forward price Ticker BB***1F(EB).

Ask forward price Ticker BB***1F(EO).

A1.2. Country Characteristics

Country characteristics are computed using data from Global Financial Data (GFD) and the Organization for Economic Cooperation and Development (OECD). Country mnemonics are as follows: United Kingdom, GBR; Switzerland, CHE; Japan, JPN; Canada, CAN; Australia, AUS; New Zealand, NZL; Sweden, SWE; Norway, NOR; Denmark, DNK; Euro area, EUR; Germany, DEU; Italy, ITA; France, FRA; Netherlands, NLD; United States, USA.

Inflation differential (INF) Difference in inflation rates for a country and the United States. Inflation rates are computed from consumer price index data from GFD (ticker CP***M); Consumer price index data for the Euro area (EA19) are from the OECD (available at https://data.oecd.org/price/inflation-cpi.htm).

Unemployment rate gap differential (UN) Difference in unemployment rate gaps for a given country and the United States. The unemployment rate 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. Unemployment rates are from GFD (ticker UN***M); the unemployment rate for the Euro area (EA19) is from the OECD (available at https://data.oecd.org/unemp/unemployment-rate.htm).

Bill yield differential (BILL) Difference in government bill yields for a given country and the United States. Government bill yields are three-month Treasury bill yields from GFD (ticker IT***3D; for the Euro area, IBEUR3D).

Note yield differential (NOTE) Difference in government note yields for a given country and the United States. Government note yields are five-year government bond yields from GFD (ticker IG***5D).

Bond yield differential (BOND) Difference in government bond yields for a given country and the United States. Government bond yields are ten-year government bond yields from GFD (ticker IG***10D).

Dividend yield differential (DP) Difference in dividend yields for a given country and the United States. Dividend yields are from GFD (ticker SY***YM; for the United Kingdom, _DFTASD; for Canada, SYCANYTM; for the Netherlands, SYNLDYAM).

Price-earnings differential (PE) Difference in price-earnings ratios for a given country and the United States. Price-earnings ratios are from GFD (ticker SY***PM; for the United Kingdom, _PFTASD; for Japan, SYJPNPTM; for Canada, SYCANPTM).

Stock market time-series momentum differential (SRET12) Difference in cumulative twelve-month stock market returns for a given country and the United States. Twelve-month cumulative returns are computed from total return indices from GFD (tickers are as follows: United Kingdom, _TFTASD; Switzerland, _SSHID; Japan, _TOPXDVD; Canada, _TRGSPTSE; Australia, _AORDAD; New Zealand, _NZGID; Sweden, _OMXSBGI; Norway, _OSEAXD; Denmark, _OMXCGID; Euro area, _DMIEU0D; Germany, _CDAXD; Italy, _BCIPRD; France, TRSBF250D; Netherlands, _AAXGRD; United States, _SPXTRD).

Idiosyncratic volatility (IV) Similarly to Filippou, Gozluklu, and Taylor (2018), we construct month-t IV as follows. We first compute daily log currency excess returns using daily spot and forward rates from Datastream for the 14 countries that we analyze. We then construct daily dollar ($\mathrm{MKT}_{\mathrm{FX}}$) and carry trade ($\mathrm{HML}_{\mathrm{FX}}$) risk factors for the Lustig, Roussanov, and Verdelhan (2011) two-factor model. The daily dollar risk factor is the cross-sectional average of the daily log currency excess returns. To construct the daily carry trade risk factor, we first sort the currencies into six portfolios based on the previous day's forward discount and take equally weighted long (short) positions in the currencies in the last (first) portfolio; the carry trade factor is the log return for the long-short portfolio. Each month, we regress daily log currency excess returns for country i on a constant and the MKT_{FX} and HML_{FX} factors:

$$rx^i_{t,d} = \alpha^i + \beta^i_{\text{MKT}_{\text{FX}},t}\text{MKT}_{\text{FX},t,d} + \beta^i_{\text{HML}_{\text{FX}},t}\text{HML}_{\text{FX},t,d} + \varepsilon^i_{t,d}, \tag{A1}$$

where $rx^i_{t,d}$ is the day-d log currency excess return for country i for month t and $\text{MKT}_{\text{FX},t,d}$ ($\text{HML}_{\text{FX},t,d}$) is the day-$d$ return for month t for the dollar (carry trade) factor. Idiosyncratic volatility is defined as

$$\text{IV}_{i,t} = \left[\frac{1}{T_{i,t}}\sum_{d=1}^{T_{i,t}}\left(\hat{\varepsilon}^i_{t,d}\right)^2\right]^{0.5}, \tag{A2}$$

where $\hat{\varepsilon}^i_{t,d}$ is the fitted ordinary least squares residual for Equation (A1) and $T_{i,t}$ is number of daily log currency excess return observations available for country i for month t.

Idiosyncratic skewness (IS) Defined as

$$\text{IS}_{i,t} = \left(\frac{1}{T_{i,t}-2}\right)\frac{\sum_{d=1}^{T_{i,t}}\left(\hat{\varepsilon}^i_{t,d}\right)^3}{\left(\text{IV}_{i,t}\right)^3}, \tag{A3}$$

where $\text{IV}_{i,t}$ is given by Equation (A2).[1]

A1.3. Global Variables

Economic policy uncertainty (EPU) Baker, Bloom, and Davis (2016) economic policy uncertainty index based on coverage frequencies in ten major US newspapers (available at https://www.policyuncertainty.com/us_monthly.html).

[1] The construction of idiosyncratic volatility and skewness follows Goyal and Santa-Clara (2003), Fu (2009), Boyer, Mitton, and Vorkink (2010), and Chen and Petkova (2012).

Monetary policy uncertainty (MPU) Baker, Bloom, and Davis (2016) monetary policy uncertainty index based on coverage frequencies in ten major US newspapers (available at https://www.policyuncertainty.com/monetary.html).

Geopolitical risk (GR) Caldara and Iacoviello (forthcoming) geopolitical risk index based on newspaper coverage (available at https://www.policyuncertainty.com/gpr.html).

Global foreign exchange (FX) volatility (GVOL) As in Menkhoff et al. (2012), month-t global FX volatility is defined as

$$\mathrm{GVOL}_t = \frac{1}{T_t} \sum_{d \in T_t} \left[\sum_{k \in K_{t,d}} \left(\frac{|\Delta s^k_{t,d}|}{K_{t,d}} \right) \right], \tag{A4}$$

where $\Delta s^k_{t,d}$ is the day-d log change in the exchange rate for country k and month t, $K_{t,d}$ is the number of currencies available for day d in month t, and T_t is the number of days in month t.

Global FX illiquidity (GILL) As in Menkhoff et al. (2012), month-t global FX illiquidity is defined as

$$\mathrm{GILL}_t = \frac{1}{T_t} \sum_{d \in T_t} \left[\sum_{k \in K_{t,d}} \left(\frac{|\mathrm{BAS}^k_{t,d}|}{K_{t,d}} \right) \right], \tag{A5}$$

where $\mathrm{BAS}^k_{t,d}$ is the day-d bid-ask exchange rate spread (in percent) for country k and month t.

Global FX correlation (GCOR) Similarly to Mueller, Stathopoulos, and Vedolin (2017), month-t global FX currency correlation is defined as

$$\mathrm{GCOR}_t = \frac{1}{N^{\mathrm{comb}}_t} \sum_{i=1}^{N_t} \left(\sum_{j>i} \mathrm{RC}^{i,j}_t \right), \tag{A6}$$

where $\mathrm{RC}_t^{i,j}$ is the realized correlation between log currency excess returns for countries i and j based on daily data for month t, N_t^{comb} is the number of combinations of currencies (i,j) for month t, and N_t is the number of available currencies for month t.

A2. Validation Methods

Conventional M-fold cross validation (e.g., as implemented in the `glmnet` package in `R`) randomly divides the observations for the training sample into M non-overlapping and generally non-contiguous blocks or folds of approximately equal size. For each value of λ in a grid, we first fit the linear model in Equation (10) from the paper via the ENet using the available observations after excluding those in the first fold; for each value of λ, we use the fitted model to compute predictions for the observations in the first fold and calculate the MSPE. Next, for each value of λ, we fit the model via the ENet using available observations after excluding those in the second fold; for each value of λ, we use the fitted model to compute predictions for the observations in the second fold and calculate the MSPE. We continue in this fashion through the remaining folds. Finally, for each value of λ, we compute the average of the MSPEs across the M folds, and we select the value of λ that minimizes the average MSPE.

A potential drawback to conventional M-fold cross validation in our context is that it does not take into account the time-series nature of panel data. Specifically, models can be fitted using observations that temporally follow those in a validation fold. To address this issue, we consider additional validation methods in a panel data context. We refer to the first as time-series validation. Suppose that we want to generate forecasts for month $t+1$ using data available through month t. We divide the panel data into observations corresponding to the first 70% and last 30% of months from the start of the sample through month t, where observations from the last 30% of months comprise the validation period. The split preserves the temporal ordering of the data. For each value of λ, we fit the linear model in

Equation (10) from the paper via the ENet using data for the first 70% of months, use the fitted model to compute predictions for the validation period, and calculate the MSPE. We select the value of λ that minimizes the MSPE.

To implement cross validation in a manner that recognizes the time-series nature of panel data, we also implement what we call time-series cross validation in a panel data context. Again suppose that we want to generate forecasts for month $t+1$ using data available through month t. We begin by using panel data observations for the first 25% of months from the start of the sample through month t to fit the linear model in Equation (10) from the paper via the ENet for each value of λ. For each value of λ, we then use the fitted model to compute predictions for panel data observations for the next 25% of months (first fold) and calculate the MSPE. Next, we use panel data for the first 50% of months from the start of the sample through month t to fit the model via the ENet for each value of λ; for each value of λ, we use the fitted model to compute predictions for panel data observations for the next 25% of months (second fold) and calculate the MSPE. In the last iteration, we use panel data for the first 75% of months from the start of the sample through month t to fit the model via the ENet for each value of λ; for each value of λ, we use the fitted model to compute predictions for panel data observations for the last 25% of months (third fold) and calculate the MSPE. Finally, for each value of λ, we compute the average of the MSPEs across the three folds, and we select the value of λ that minimizes the average MSPE.

Table A1 reports R^2_{OS} statistics for Linear-ENet forecasts that use different methods for tuning λ. The values in the fourth through seventh columns are typically less than the corresponding values in the fifth column of Table 2 from the paper.

A3. The US Dollar As a Safe-Haven Currency

A spate of recent papers (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 based on the US dollar's perception as a safe-haven currency. Due to data availability, these studies analyze predictability at a quarterly horizon or longer and/or employ relatively short samples. Although we focus on a monthly horizon and consider a longer out-of-sample period, our machine learning forecasts appear to capture exchange rate predictability around the crisis relating to a safe-haven role for the US dollar. Specifically, the Linear-ENet and DNN forecasts in Figures 2 and 3, respectively, from the paper portend strong depreciations for many countries' currencies in late 2008 during the worst phase of the crisis; as shown in Figure 4 from the paper, the machine learning forecasts substantially outperform the no-change benchmark during that time.

We also examine links between the set of predictors selected by the Linear-ENet and Lilley et al. (forthcoming) capital flow measure, which is available at the quarterly frequency and is based on the change in US holdings of foreign bonds. Lilley et al. (forthcoming) find that their measure is significantly related to various proxies for global risk appetite, as well as the change in a broad US dollar index from 2007 to 2017, which they interpret as evidence of the US dollar's role as a safe-haven currency during the crisis. We investigate links between the eight predictors selected by the Linear-ENet in the fitted panel predictive regression based on data through 2020:08 (corresponding to the forecast for the final month, 2020:09) and the change in US foreign bond holdings.[2] We average the eight predictors over the three months comprising a quarter, as well as across countries. We then regress the change in US foreign bond holdings on the set of eight time- and country-aggregated predictors for 2007:1 to 2019:2.[3]

Figure A1 shows the (standardized) change in US foreign bond holdings, together with the fitted values for the regression. As a group, the eight predictors selected by the Linear-ENet are significantly related to the change in US foreign bond holdings at the 1% level, and

[2]The eight predictors selected by the ENet are UN, DP, INF.GVOL, BILL.GVOL, PE.EPU, PE.GILL, SRET12.MPU, and IV.GCOR.

[3]Data for the change in US foreign bond holdings from Lilley et al. (forthcoming) are available from the Global Capital Allocation Project website.

the predictors collectively explain nearly 40% of the variation in the capital flow measure. The fitted values track the actual values quite closely during the Global Financial Crisis, providing further evidence that relevant predictors selected by the ENet contain information pertaining to a safe-haven role for the US dollar.

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Table A1: R^2_{OS} Statistics (%) for Different Validation Methods

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% level, respectively, according to the Clark and West (2007) test. The fourth through seventh columns report results for Linear-ENet forecasts that use five-fold cross validation, time-series validation, time-series cross validation, and the BIC, respectively, to tune the regularization parameter, as described in Section A2.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Country	Out-of-Sample Period	Obs.	5-fold CV	TSV	TSCV	BIC
United Kingdom	1995:01–2020:09	309	−2.10	0.74*	1.15**	2.55**
Switzerland	1995:01–2020:09	309	−2.70	−0.90	1.24**	0.29*
Japan	1995:01–2020:09	309	−3.25	−0.66	0.80**	−0.39
Canada	1995:01–2020:09	309	−8.72	−2.48	−1.18	−2.09
Australia	1995:01–2020:09	309	−2.15	−0.58	0.10	0.44*
New Zealand	1995:01–2020:09	309	−1.43	0.41	0.62	2.36**
Sweden	1995:01–2020:09	309	−1.30	1.97**	1.35**	1.74**
Norway	1995:01–2020:09	309	−1.41	1.30**	1.36**	1.15**
Denmark	1995:01–2020:09	309	0.85***	0.67**	1.42***	1.92***
Euro area	2000:02–2020:09	248	−4.62	−2.77	−0.11	0.83**
Germany	1995:01–1998:12	48	−5.78	−1.27	0.11	−0.09
Italy	1995:01–1998:12	48	−5.59	−0.05	0.24**	−0.74
France	1995:01–1998:12	48	−17.61	−2.73	0.40	−0.40
Netherlands	1995:01–1998:12	48	−6.17	0.69	−0.46	0.28
All	1995:01–2020:09	3,221	−2.69	−0.10	0.70***	0.92***

Table A2: R^2_{OS} Statistics (%) for Benchmark Based on INF and UN

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 benchmark forecast; for the positive R^2_{OS} statistics, *, **, and *** indicate that the reduction in MSPE is significant at the 10%, 5%, and 1% level, respectively, according to the Clark and West (2007) test. The Linear-ENet, DNN, and ensemble forecasts incorporate the information in 70 predictors. The benchmark forecast is based on a linear panel predictive regression with INF and UN as predictors estimated via OLS.

(1)	(2)	(3)	(4)	(5)	(6)
Country	Out-of-sample period	Obs.	Linear-ENet	DNN	Ensemble
United Kingdom	1995:01–2020:09	309	2.94*	3.12**	3.42**
Switzerland	1995:01–2020:09	309	0.83	2.45**	1.56*
Japan	1995:01–2020:09	309	−0.50	1.05	0.43
Canada	1995:01–2020:09	309	−1.44	−0.43	−0.93
Australia	1995:01–2020:09	309	0.55	1.11*	0.61
New Zealand	1995:01–2020:09	309	1.84*	2.10**	2.02*
Sweden	1995:01–2020:09	309	2.62**	2.31**	2.18*
Norway	1995:01–2020:09	309	2.25**	1.49*	1.82*
Denmark	1995:01–2020:09	309	2.42**	1.95***	2.08***
Euro area	2000:02–2020:09	248	1.00*	1.36***	1.48**
Germany	1995:01–1998:12	48	0.67	0.06	−0.35
Italy	1995:01–1998:12	48	0.85	2.95**	1.40
France	1995:01–1998:12	48	2.40*	3.24**	2.74**
Netherlands	1995:01–1998:12	48	1.84	1.28	1.18
All	1995:01–2020:09	3,221	1.33***	1.71***	1.49***

Table A3: R^2_{OS} Statistics (%) for Benchmark Based on INF and BILL

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 benchmark forecast; for the positive R^2_{OS} statistics, *, **, and *** indicate that the reduction in MSPE is significant at the 10%, 5%, and 1% level, respectively, according to the Clark and West (2007) test. The Linear-ENet, DNN, and ensemble forecasts incorporate the information in 70 predictors. The benchmark forecast is based on a linear panel predictive regression with INF and BILL as predictors estimated via OLS.

(1)	(2)	(3)	(4)	(5)	(6)
Country	Out-of-sample period	Obs.	Linear-ENet	DNN	Ensemble
United Kingdom	1995:01–2020:09	309	3.58^{**}	3.76^{**}	4.06^{**}
Switzerland	1995:01–2020:09	309	0.69	2.32^{**}	1.43^{*}
Japan	1995:01–2020:09	309	−0.38	1.17	0.55
Canada	1995:01–2020:09	309	0.34	1.33^{*}	0.84
Australia	1995:01–2020:09	309	1.16^{*}	1.72^{**}	1.22^{**}
New Zealand	1995:01–2020:09	309	2.34^{*}	2.60^{**}	2.52^{**}
Sweden	1995:01–2020:09	309	3.02^{**}	2.72^{**}	2.58^{**}
Norway	1995:01–2020:09	309	2.57^{**}	1.81^{*}	2.15^{**}
Denmark	1995:01–2020:09	309	2.88^{***}	2.42^{***}	2.55^{***}
Euro area	2000:02–2020:09	248	1.13^{*}	1.49^{**}	1.61^{**}
Germany	1995:01–1998:12	48	0.17	−0.44	−0.86
Italy	1995:01–1998:12	48	2.16	4.24^{*}	2.71
France	1995:01–1998:12	48	1.72^{*}	2.56^{**}	2.05^{*}
Netherlands	1995:01–1998:12	48	1.56	1.00	0.91
All	1995:01–2020:09	3,221	1.75^{***}	2.12^{***}	1.91^{***}

Table A4: Portfolio Performance for Non-US Investors

The table reports portfolio performance metrics for a mean-variance investor in the domestic country in the first column with a relative risk aversion coefficient of five who allocates monthly across available currencies using the ensemble exchange rate forecast when predicting the currency excess return. The out-of-sample period is 1995:01 to 2020:09. The ensemble exchange rate forecast is the average of Linear-ENet and DNN forecasts based on the information in 70 predictors. The exchange rate forecast (foreign currency units per unit of domestic currency) is implied by the relevant US dollar exchange rate forecasts (i.e., foreign currency units per US dollar and domestic currency units per US dollar). The second column reports the annualized increase in certainty equivalent return when the investor uses the ensemble exchange rate forecast in lieu of the no-change benchmark. Statistical significance for the Sharpe ratio is based on the Bao (2009) procedure; *, **, and *** indicate significance at the 10%, 5%, and 1%, level, respectively.

(1) Domestic Investor	(2) Annualized Average Utility Gain	(3) Annualized Mean	(4) Annualized Volatility	(5) Annualized Sharpe Ratio
United Kingdom	2.83%	9.67%	11.77%	0.82^{***}
Switzerland	−1.36%	6.88%	14.62%	0.47^{**}
Japan	1.71%	9.80%	12.67%	0.77^{***}
Canada	2.50%	8.98%	11.65%	0.77^{***}
Australia	2.06%	9.48%	11.45%	0.83^{***}
New Zealand	1.93%	9.62%	14.18%	0.68^{***}
Sweden	2.42%	9.90%	10.96%	0.90^{***}
Norway	2.47%	9.48%	11.50%	0.82^{***}
Denmark	1.01%	7.94%	11.49%	0.69^{***}

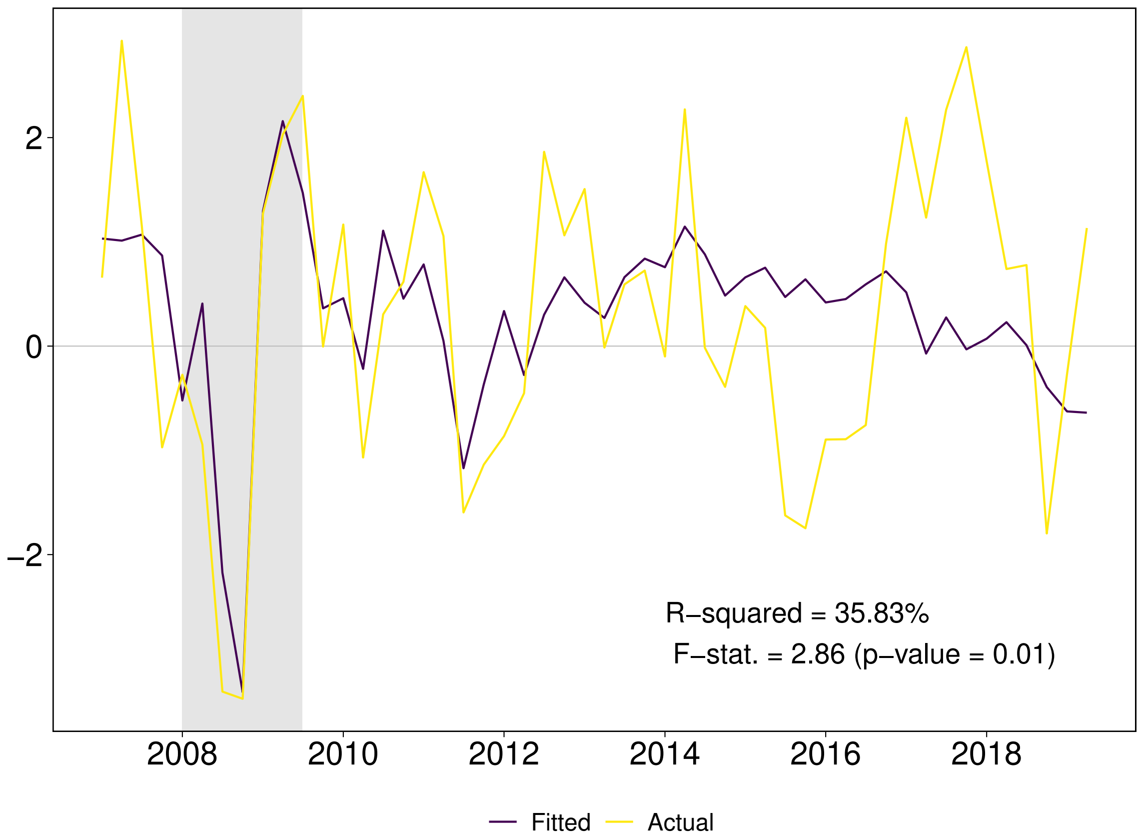

Figure A1. Change in US foreign bond holdings. The figure shows actual and fitted values for a regression of the (standardized) change in US foreign bond holdings on the eight predictors selected by the Linear-ENet (UN, DP, INF.GVOL, BILL.GVOL, PE.EPU, PE.GILL, SRET12.MPU, IV.GCOR). Vertical bars delineate business-cycle recessions as dated by the National Bureau of Economic Research.