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Exchange rate expectation, abnormal returns, and the COVID-19 pandemic*

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Abstract

This study analyzes the impact of the COVID-19 pandemic on exchange rates based on a comprehensive set of survey forecasts for more than 50 currency pairs. At the first stage, we assess whether the policy to manage the COVID-19 pandemic affects the expected path of exchange rates over the medium and long run. At the second stage, we adopt an event study analysis and identify the occurrences of abnormal returns on foreign exchange markets since the start of the COVID-19 pandemic. Our results suggest the presence of cumulated excess returns that are partly driven by macroeconomic fundamentals for major currencies. However, we find that policy responses to the COVID-19 pandemic have the strongest effect on cumulated excess returns, showing that foreign exchange markets take expected policy effects as an important determinant of future developments into account while expectations for minor currencies react stronger to response policies.

Keywords: Abnormal returns, COVID-19 pandemic, Exchange rates, Expectations, Survey data
JEL: F31, F37, G41

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1 Introduction

The response of financial markets to the COVID-19 pandemic has attracted great interest among researchers. Stock markets recovered quickly from an initial sharp drop and currency markets have also shown some distinctive patterns. Gräb *et al.* (2021) show that positive information about vaccine news increases the price of assets which experienced a drop in prices and has a positive net effect on financial conditions. An increase in confirmed COVID-19 cases also significantly raises exchange rate volatility which initially increased in 2020 (Feng *et al.*, 2021). However, currency markets remained overall stable in 2020 which also reflects the global scale of the pandemic given that bilateral dollar exchange rates mirror information about two economies. While recent research has focused on spot market movements over the COVID-19 period, little is known about the expected path of exchange rates during the pandemic. A general perspective on exchange rate movements can be derived based on the framework of Engel and West (2005) which argues that the exchange rate can be expressed as the discounted sum of observable and unobservable macroeconomic fundamentals. The fact that exchange rates are expressed in relative terms opens up an interpretation in terms of the expected economic effects of the pandemic. Given their importance for macroeconomic outcomes over this period, policy measures conducted during the pandemic potentially play an important role in this regard. Consequently, the path of dollar exchange rates should also incorporate the effects of domestic lockdown policies relative to the US. Hence, exchange rate expectations can be of particular relevance for the transmission of information or policy shocks. They can propagate credible policy announcements and decisions but disagreement and forecast errors in the aftermath of policy actions can also result in substantial uncertainty.

The rich literature on exchange rate expectations has already addressed several questions ranging from determinants of individual forecasts to the adequacy of individual forecasts (Menkhoff *et al.*, 2009; Beckmann, 2021; Iregui *et al.*, 2021). Existing evidence based on survey data suggests that exchange rate forecasters rely on different models and often make substantial forecast errors (Jongen *et al.*, 2012; Goldbaum and Zwinkels, 2014). The notorious exchange disconnect puzzle makes exchange rate forecasting extremely difficult and recent evidence has illustrated the relevance of information rigidities in the context of exchange rates expectations (Sarno, 2005; Beckmann and Reitz, 2020).

The pandemic reflects a period of substantial uncertainty and an interesting feature of foreign exchange markets in such periods is that particular currencies act as a safe haven. Over the recent period, only some currencies, such as the Japanese yen and the euro, appreciated against the US dollar. A striking and unexpected feature of the 2008/2009 global financial crisis has been the sharp appreciation of the US dollar against virtually all currencies globally. Fratzscher (2009) points out that negative US-specific macroeconomic shocks during the crisis triggered an US dollar appreciation, rather than a depreciation as a result of a flight-to-safety phenomenon in which investors shifted portfolios into US equities and bonds. He finds that currencies of countries with high financial exposure to the US, with low FX reserves and a high current account deficit have experienced stronger responses to US shocks during the financial crisis. Other currencies, such as the Swiss franc and the Japanese yen, are also known to gain value in times of uncertainty (Hossfeld and MacDonald, 2015).

An interesting question related to expectations is whether such effects are expected by market participants or reflect unexpected market returns. Given that exchange rate expectations are strongly linked to future expected effects of the pandemic relative to the US, we contribute to the literature by analyzing the effect of the pandemic on foreign exchange markets from two new perspectives. We assess (i) how exchange rate expectations are formed during the pandemic and (ii) whether and how response policies to the pandemic affect the foreign exchange market when taking expectations into account. This is important given that expectations can amplify policy shocks via affecting the actual path of the exchange rate. In this context, we also distinguish between major and minor currencies given that minor currencies are often strongly affected by global factors and are not fully controlled by domestic policymakers. We start by assessing exchange rate expectations over different forecasting horizons, taking the policy response to COVID-19 as determinants into account. Policies conducted during the pandemic may have a direct effect on exchange rates since an expected stable path of an economy during the pandemic can attract global capital flows.

While this part of our analysis provides insights into expectation building during the pandemic, it does not account for realized exchange rate changes. In a second step, we therefore examine the occurrences of abnormal returns on foreign exchange markets since the start of the COVID-19 pandemic based on an event study analysis following Linton (2019). We use the period from January 2020 to December 2020 as an event window, which is expected to show different behavior on foreign exchange markets due to the COVID-19 pandemic. In doing so, we basically compare the observed exchange rate changes over the entire year 2020 with those that were expected by market participants one or two years prior. At the time market participants formed their expectations, COVID-19 did not exist and therefore, the event occurrence is clearly exogenous to exchange rate movements. We also compare abnormal returns realized within the COVID-19 pandemic period with those observed around the global financial crisis.

Our analysis enables us to distinguish between expected and unexpected effects of the pandemic on exchange rate expectations. We provide evidence for abnormal returns during the pandemic and we find that these excess returns can partly be explained by macroeconomic fundamentals, such as inflation and currency reserves. Our findings suggest that these excess returns result from sluggish adjustment of expectations to shocks during the pandemic. In addition, we also find that policy responses to COVID-19 have a strong effect on these returns.

The remainder of the paper is organized as follows. Section 2 provides a review of the related literature, Section 3 presents the data and the empirical strategy and Section 4 discusses the empirical findings. Section 5 concludes.

2 Literature Review

We contribute to several strands of the literature on exchange rates. Given the rich literature, this section briefly summarizes selective studies which mostly relate to our research question.

Starting with the general adoption of exchange rate surveys, several studies have analyzed exchange rate expectations based on surveys of professional forecasters. Early studies focused on their forecasting ability as well as on drivers of expectations. Blake *et al.* (1986) and Chinn and Frankel (1994) have shown that professionals make substantial mistakes when forecasting exchange rates, a finding which has been confirmed by several subsequent studies. Recent work by Beckmann and Reitz (2020) has illustrated that forecast errors do not point to unbiasedness and information efficiency and can rather be explained by models related to information rigidities.

Noisy information is of particular relevance since it reflects the complexity of exchange rate dynamics. Formally, the underlying idea is that individual forecasters, denoted by i, can solely observe a noisy signal s^*_{it} of the exchange rate which consists of the true spot rate s_t, a common shock ν_t and an individual-specific shock ϵ_{it}. The common shock term ν_t reflects the short-run fluctuations while the individual disturbance term ϵ_{it} is independently and identically distributed across forecasters (Coibion and Gorodnichenko, 2012; Beckmann and Reitz, 2020). Such a formulation can resemble several empirical patterns, such as predictable forecast errors and fluctuations in disagreement among forecasters. In the context of our paper, it can explain why forecasters might for example respond differently to policy actions during the pandemic even if a strong response of the mean forecast is not observed. Depending on their individually perceived noisy signals, some participants might expect an appreciation while others expect the exchange rate to depreciate.[1]

While we are the first to assess the interplay of exchange rate expectations, policy actions and excess returns during the pandemic, previous studies have assessed currency markets during the global financial crisis (GFC). Beckmann and Czudaj (2017) analyze exchange rate forecasts for 30 major and 35 minor currencies for the period after the start of the GFC, focusing on the performance of professional forecasts and the time-varying impact of macroeconomic fundamentals on expectations. Their findings show that the safe haven status of the US dollar after 2009 was largely unexpected.

The excess returns we analyze stem from a deviation between expected and realized spot rates. An interesting question refers to drivers of these excess returns. The findings by Fratzscher (2009) show that exchange rate changes during the GFC can partly be explained by macroeconomic fundamentals. This finding relates to theoretical models and empirical regularities of exchange rate behavior. The link between exchange rates and macroeconomic fundamentals is nonlinear and subject to structural breaks, a finding which can be explained by the scapegoat approach introduced by Bacchetta and van Wincoop (2004, 2006, 2013) that relates unexpected exchange rate changes to unexpected changes in fundamentals. An interesting difference between the pandemic

[1] Another line of research which might offer an explanation for unchanged mean forecasts has focused on herding among forecasters (see e.g. Fritsche *et al.*, 2015, among others).

and the GFC corresponds to the policy responses. Monetary policy sharply decreased interest rates in 2008, entering the period of unconventional monetary policy. Given the nature of the shock and the monetary environment, responses to the COVID-19 pandemic have been accompanied by monetary policy but other policy actions related to lockdowns, government responses and health policy have been more important. Therefore, it is also interesting to compare patterns of excess returns between the GFC and the COVID-19 pandemic.

3 Data and Empirical Methodology

3.1 Data

The present study relies on survey-based monthly exchange rate expectations data over two forecast horizons (12-month and 24-month) provided by FX4casts (see `http://www.fx4casts.com/`). The consensus is based on individual responses of 48 professionals, mostly banks,[2] and is aggregated to a single composite forecast for each currency by taking the mean across forecasters. Spot rates and their expectations are measured in units of domestic currency per one unit of the US dollar (i.e. a decrease corresponds to an appreciation of the domestic currency) and are provided for 29 major currencies and 33 minor currencies according to the FX4casts classification as listed in Table A.1. For each currency, the start of the sample period is also reported in Table A.1. We include currencies with managed floating exchange rate regimes or close to fixed exchange rate regimes, but we ensure that we only include exchange rates which display some

[2]The contributors include: Allied Irish Bank, ANZ Bank, Bank of America/Merrill Lynch, Bank of New York Mellon, Barclays Capital, Bayerische Landesbank, BNP Paribas, Canadian Imperial Bank of Commerce, Credit-Agricola, Citigroup, Commerzbank, Credit Suisse - First Boston, Danske Bank, Deka Bank, Deutsche Bank, DnBNOR, The Economist - Intelligence Unit, Goldman Sachs, Handelsbanken, HSBC, IHS Global Insight, ING Bank, Intesa Sanpaolo, JP Morgan Chase, Julius Baer, Lloyds TSB, Macquarie Capital Securities, Moody's Economy.com, Morgan Stanley, National Australia Bank, Nomura, Nordea, Rabobank, Royal Bank of Canada, Royal Bank of Scotland, Scotiabank, SEB, Societe Generale, Standard Chartered, Suntrust, Swedbank, Bank of Tokyo-Mitsubishi UFJ, Toronto Dominion, UBS Warburg, UniCredit, Vontobel, Wachovia, and Westpac.

fluctuations over the sample period. The sample period runs until December 2020 on a monthly basis and we specifically focus on the period from January 2020 to December 2020 but we also use data prior to this period as will be outlined below.

In addition, we use COVID-19 Government Response Tracker as a possible determinant of exchange rates and exchange rate expectations. The Oxford COVID-19 Government Response Tracker (OxCGRT) enables us to compare policy responses to the pandemic across countries. The root idea is to record the number and strictness of government policies. The OxCGRT is based on publicly available information on 20 indicators for more than 180 countries[3] but we focus on a small set of relevant indicators which are (i) relevant from an economic point of view and (ii) fluctuate over time. We include an overall government response index, which records how the response of governments has varied over all indicators in the database, a containment health index, which summarizes different policy response indicators (including school closures, workplace closures, travel bans, testing policy, contact tracing, face coverings, and vaccine policy), and the original stringency index, which records the strictness of 'lockdown style' policies. We also consider a stringency index which is essentially a reduced version of the stringency index (i.e. the stringency legacy index). All measures are re-scaled to a value from 0 to 100 as the strictest policy. The main advantage of these measures is that they are comparable across countries.

We pay special attention to the timing of the exchange rate surveys. Each month, participants are asked to provide their expectations two days before the publication of the survey. We use these dates as a benchmark to assess the impact of the OxCGRT on exchange rate expectations by analyzing the response measures between these two dates. Exchange rate forecasts always correspond to the end of period. Therefore,

[3]See `https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker` for further details.

we use end of month exchange rates from the International Monetary Fund (IMF) to compute excess returns. Spot rates on the day of the survey (i.e. when expectations are made) required to calculate expected exchange rate changes are also provided by FX4casts.

Macroeconomic fundamentals used to explain excess returns have been accessed from different sources as follows. While we focus on realized values for currency reserves and short-term interest rates from the IMF, we use growth forecasts from the Organisation for Economic Co-operation and Development (OECD) given the unavailability of realized data for all countries. In addition, we rely on the Morgan Stanley Capital International (MSCI) index as stock market measure for all countries. Compared to Fratzscher (2009), our set of fundamentals is partly restricted by data availability. Financial liabilities vis-à-vis the US are for example not available for all countries under consideration. However, our set of regressors includes an established set of macroeconomic fundamentals related to the path of the economy, policy choices and financial markets.[4]

3.2 Empirical Methodology

At the first stage, we focus on the effect on expected exchange rate changes $E_t(\Delta s_{i,t+h})$ measured by the relative difference between the expected exchange rate defined as the

[4]Following an advice from a referee, we have also considered to match measures of volatility and/or trading volume with expectations. There are several issues when it comes to practical implementation of such an analysis. We have contacted the Continuous Linked Settlement (CLS) bank which provides the most accurate data on trading volume at higher frequencies to get hold of adequate data (see e.g. Ranaldo and Somogyi, 2021). However, the availability of the corresponding data is restricted both in terms of currencies (only 33 currency pairs) as well as sample period (no data prior to 2011). As a result, we have not conducted an explicit analysis which includes trading volumes. However, we have compared the trading volumes before and after the pandemic and found that standard deviation, skewness and kurtosis all increased during the pandemic. This indicates changes in the currency markets during the pandemic.

mean forecast across forecasters and its current spot rate for horizon h with $h = 12, 24$

$$E_t(\Delta s_{i,t+h}) = 100 \frac{E_t(s_{i,t+h}) - s_{i,t}}{s_{i,t}}, \tag{1}$$

where $E_t(.)$ is the expectation conditional on the information available at time t, $i = 1, \ldots, n$ stands for the corresponding currency as the cross-section unit and $s_{i,t}$ is the spot rate at the time t the expectations are made. For the sample period from January 2020 to December 2020, we examine whether these expected exchange rate changes are effected by the COVID-19 policy indicators based on the following equation

$$E_t(\Delta s_{i,t+h}) = \beta \text{COVID-19}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}, \tag{2}$$

where we also include country and time fixed effects μ_i and λ_t, respectively, to account for unobservable heterogeneity. As we consider bilateral dollar exchange rates, the COVID-19 policy indicators COVID-$19_{i,t}$ are taken as differences compared to the US.

Having assessed the effect on exchange rate expectations, we conduct an event study analysis[5] following Linton (2019) and use the period from January 2020 to December 2020 as event window, which is expected to show different behavior on foreign exchange markets due to the COVID-19 pandemic.[6] The estimation window, which in our case is required to estimate the variance of the (abnormal) exchange rate return as will be outlined below, is set to ten years prior to the outbreak of COVID-19 and therefore runs from January 2010 to December 2019. The selection of this period is driven by different considerations. First of all, we want to ensure that the estimation window is

[5]An alternative approach would be to apply a difference-in-differences regression, which is not feasible in our case as this approach requires a control group of currencies within the treatment period that is unaffected by the treatment. The treatment in our case is the COVID-19 pandemic and as all countries in the world are affected by the pandemic, we do not have any untreated currencies.

[6]The first COVID-19 case already occurred on December 1, 2019 in China. Therefore, it might have been possible to start the event window in December 2019. However, we decided to start in January 2020 due to the fact that at the very beginning of the COVID-19 outbreak it was not considered as a pandemic as it just emerged in a single region in China (the WHO declared it as a pandemic in March 11, 2020) and the consequences have not been foreseeable by professional FX forecasters at December 2019.

long enough to enable us to reliably estimate the variance of returns. Second, we also aim to include as many currencies as possible and finally, we do not want the estimation window to be contaminated by the global financial crisis (GFC) around the years 2007, 2008 and 2009.[7] In the following we will also use a second event study analysis to assess the impact of the GFC as a comparison to the findings of the COVID-19 event study.

Usually the estimation window is used to estimate a model (e.g. the market model) based on which one can forecast the returns of an asset for the event window against which the observed returns are compared to compute 'abnormal' returns. In this study, however, we do not estimate any model but we instead rely on the aggregate mean forecast across professional forecasters as our proxy for market expectations. More precisely, abnormal returns (or unexpected returns) are measured as the difference of the observed percentage exchange rate change over a horizon of 12 months (or 24 months) and the expected percentage change over the same horizon by professionals

$$AR_{i,t,12} = 100\left[\frac{s_{i,t+12} - s_{i,t}}{s_{i,t}} - \frac{E_t(s_{i,t+12}) - s_{i,t}}{s_{i,t}}\right] = 100\frac{s_{i,t+12} - E_t(s_{i,t+12})}{s_{i,t}}, \qquad (3)$$

where $s_{i,t}$ represents the spot rate of currency i at period t and $E_t(.)$ denotes the expectation conditional on the information available at time t. As discussed earlier, the existing literature has widely rejected unbiased exchange rate expectations, giving room for excess returns based on the above equation. However, little is known about the determinants and dynamics of these excess returns based on survey data.

[7] In this context it should be noted that the estimation window also includes the European debt crisis between 2010 and 2012. However, in contrast to the GFC, which had a severe impact on all economies around the globe and therefore, on all exchange rates, the European debt crisis had only an effect on one exchange rate in our data set – the EUR/USD rate. Therefore, the European debt crisis is less likely to contaminate our results compared to the GFC. As will be outlined below, the sample period from 2010 to 2019 is solely used to consistently estimate the variance of (abnormal) exchange rate returns, which is needed for testing whether these significantly differ from zero within the event window (January to December 2020). Therefore, to confirm the robustness of our findings we have also re-run the same test for the EUR/USD rate using the variance estimated from the sample period from 2013 to 2019. The corresponding findings are not reported to save space but these do not differ from the ones presented below. The additional findings are available upon request.

We rely on a forecast horizon of 12 months, as demonstrated in Eq. (3), and 24 months. This allows us to compare the observed exchange rate changes over the entire year 2020 (i.e. the event window) with those that were expected by market participants one ($h = 12$) and two years prior ($h = 24$). At the time market participants formed their expectations, COVID-19 did not exist and therefore, the event occurrence is clearly exogenous to exchange rate movements. Shorter forecast horizons are also available within the FX4casts data set ($h = 1, 3, 6$) and could also be used. However, we declined to use them because in this case we would have been limited assessing the effect of COVID-19 for a (much) smaller event window. When, for instance, using a horizon of 6 months, then we would have only studied the impact of the pandemic for the event window from January 2020 to June 2020 as the following 6-month forecasts were already made after the outbreak of the pandemic.[8]

As a next step, the abnormal returns $AR_{i,t,12}$ are cumulated over the event window, $t = 1, \ldots, T^*$, to get $CAR_{i,12} = \sum_{t=1}^{T^*} AR_{i,t,12}$. Then, we test the null of no effect as $CAR_{i,12} = 0$. Under the null, we assume abnormal returns $AR_{i,t,12}$ to be normally distributed with a zero mean and a constant variance $\sigma^2_{i,12}$. Therefore, $CAR_{i,12} \sim N(0, T^* \sigma^2_{i,12})$ and we require an estimate for $\sigma^2_{i,12}$ to conduct inference. As already mentioned above this variance has been estimated for the estimation window. As inference depends on the normality assumption, we, first of all, test for normality within the estimation window to justify the assumption[9] and second, we also aggregate $CAR_{i,12}$

[8] It should also be noted that generally higher frequency data is more appropriate to capture effects stemming from specific events. However, in contrast to any one-time event that occurred on a specific day, in our study the event is the COVID-19 pandemic, which lasts since its outbreak. Therefore, in our case the lower monthly frequency seems to be appropriate. In addition, survey-based exchange rate expectations data is solely available on a monthly frequency and this is particularly beneficial in our context as this enables us to compare realized exchange rates during the COVID-19 pandemic with exchange rate expectations that were formed prior to the outbreak of the COVID-19 pandemic. This would not been possible when relying on daily or intraday data.

[9] In this context it should be emphasized that to check for normality of abnormal returns $AR_{i,t,12}$ (or $AR_{i,t,24}$) prior to the outbreak of the COVID-19 pandemic and to estimate the variance of these returns $\sigma^2_{i,12}$ that is required for the testing $CAR_{i,12} = 0$, we compute abnormal returns as shown in

across currencies i which provides a consistent test without assuming normality (Linton, 2019)

$$CAR_{12} = \sum_{i=1}^{N} \sum_{t=1}^{T^*} AR_{i,t,12}. \tag{4}$$

It is important to highlight that such a test differs from conventional tests for unbiasedness in the literature as summarized by Jongen *et al.* (2008). Such tests analyze whether exchange rate expectation are perfect predictors of the future spot rate. Cumulative excess returns could still be normally distributed when professionals make positive and negative errors over time. Hence, not rejecting normality does not imply that professional forecasts are accurate.

Tables A.2 and A.3 provided in the Appendix report the results of normality tests for abnormal returns and also of tests checking the null of means equal to zero for major and minor currencies over a 12- and 24-month horizon. First of all, for major currencies the null of a zero mean can solely be rejected for three currencies at the 5% level over the 12-month horizon (TRY, INR and ARS). This finding is confirmed for minor currencies as only two currencies show means significantly different from zero (LBP and LKR). Second, the null of normality can be rejected for only ten out of 29 major currencies over the 12-month horizon based on the Jarque-Bera test. This shows that the normality assumption is roughly valid for two-thirds of the major currencies. For minor currencies the findings are less clear-cut as for 19 out of 32 minor currencies, the normality assumption is rejected. For the 24-month horizon the results are mostly equivalent but we find more evidence for non-zero returns for important major currencies, such as the British pound, the Japanese yen, and the Mexican peso.

Eq. (3) but solely for the estimation window from January 2010 to December 2019. Then, using these returns normality tests are conducted as reported in Tables A.2 and A.3 in the Appendix and the variance is estimated as $\widehat{\sigma}^2_{i,12} = \frac{1}{T-1}\sum_{t=1}^{T}\left(AR_{i,t,12} - \overline{AR}_{i,12}\right)^2$. 95% confidence intervals for $CAR_{i,12}$ are then computed as $CAR_{i,12} \pm 1.96\sqrt{T^*}\widehat{\sigma}_{i,12}$, where T^* is the length of the event window.

4 Empirical Results

4.1 Cumulative Abnormal Returns

Cumulative abnormal returns (CAR) are visualized in Figures 1 and 14 for different currencies and different aggregations across currencies together with their 95% confidence intervals. Figure 1 illustrates that abnormal returns over a horizon of 12 months aggregated over different major currency groups clearly differ from zero and increase over the event window. This trend is strongest for (Latin) American currencies and weakest for Asian currencies. Figures 2 and 4 provide the corresponding findings for individual currencies. Many graphs of individual currency pairs display a similar trend, but the confidence intervals embrace the zero line in several cases, which indicates that the null of no effect cannot be rejected for all currencies. However, significant abnormal returns are also observed for the Hungarian forint, the Norwegian krone, the Turkish lira (see Figure 2), the Australian dollar, the New Zealand dollar, the Philippine peso, the Taiwan dollar (see Figure 3), all Latin American currencies considered and the South African rand (see Figure 4) over the 12-month horizon. Over the 24-month horizon the results are much more in favor of significant abnormal returns both on an aggregate (see Figure 5) and on an individual level (see Figures 6 to 8). In this case nearly all currencies show significant excess returns.[10] Exceptions include the Swiss franc, the Japanese yen and the Canadian dollar. Figure 9 also visualizes abnormal returns for minor currencies, which basically confirms the previous findings as minors exhibit abnormal returns that are insignificant over the 12-month horizon but signifi-

[10] In this context, it should also be noted that contagion between markets is very likely, in particular since all exchange rates are linked via cross-country arbitrage and since we study the effect of a global phenomenon – the COVID-19 pandemic – on foreign exchange markets. Given that all exchange rates are expressed relative to the US dollar, we implicitly account for common movements across countries. However, to address the role of contagion explicitly goes beyond the scope of the present study. Therefore, the findings should also be interpreted with caution due to a possible effect of contagion.

cantly different from zero at the 5% level over the 24-month horizon. The Appendix also provides graphs for individual abnormal returns for all minor currencies.

*** Insert Figures 1 to 9 about here ***

For comparison, Figures 10 to 14 illustrate abnormal returns observable around the GFC from July 2008 to January 2009 over a 12-month horizon. We also provide evidence in favor of significant abnormal returns during the GFC period. The main difference, however, is that we also observe significantly negative abnormal returns, especially for European and minor currencies, in contrast to the COVID-19 pandemic period.

*** Insert Figures 10 to 14 about here ***

Overall, we provide evidence in favor of significant excess returns, at least for some currencies. These results align with the existing literature on the adequacy of exchange rate surveys in terms of point forecasts. The results in the next section will shed some light on the question whether the identified excess returns reflect unexpected spot rate movements or changes in expectations relative to the spot rate. We disregard minor currencies for parts of the remaining analysis due to lack of data availability for some countries.

4.2 Determinants of Expected Exchange Rate Changes

To understand exchange rate dynamics and expectation building during the pandemic, we proceed by assessing the question whether the lockdown COVID-19 indicators explain expected exchange rate changes over 12 and 24 months. We conduct these estimates with indicators calculated relative to the US and report the findings in Table 1. However, the results are fairly robust with regard to an alternative configuration with only domestic indicators. We provide separate regressions for each indicator in order to assure that our results are not affected by multicollinearity as the COVID-19 indicators are highly correlated.

*** Insert Table 1 about here ***

The results reported in Table 1 show that the different indicators do not seem to have systematic effects when accounting for country and time fixed effects. For major currencies, there is only borderline significance at the 10% level for the stringency legacy index over a horizon of 24 months. Results for minor currencies display much more significance with all indicators except the government response index displaying significance over the 12-month horizon. For the 24-month horizon solely the stringency legacy as well as the containment index show significance. All coefficients are positive, pointing to an expected depreciation in case of more restrictive policies. This finding also holds if only domestic lockdown policies instead of differentials to the US are taken into account.

The slightly more significant effects for minor currencies might reflect the perception that US policies are the dominant drivers of exchange rate dynamics, suggesting that small open economies are often unable to conduct independent exchange rate or monetary policy (Miranda-Agrippino and Rey, 2021). This would suggest that US response policies are considered a clear signal for minor currencies while major currency forecasts are complicated by policy signals from two economies. Another possible explanation for these results besides country- and time-specific effects is that professionals heavily rely on the spot rate when forecasting exchange rates, particularly in times of uncertainty. Table A.4 provided in the Appendix displays unconditional correlations between spot rates and expected exchange rates. It turns out that the correlation is indeed quite high and mostly exceeds 0.9. Given the existing evidence that random walk forecasts often dominate fundamental exchange rate models (Meese and Rogoff, 1983), this result is not surprising. For some currencies, the high correlation can also be explained by managed exchange rate regimes which limit exchange rate fluctuations. However, this might only partly explain the (mostly) insignificant effects of lockdown policies on exchange rate expectations for major currencies given that only correlations for a small number of minor currencies are significantly smaller than 0.9.

4.3 Determinants of Cumulative Abnormal Returns

Finally, we turn to the regression results for cumulative abnormal returns (CAR), starting with the effect of macroeconomic fundamentals. The literature proposes several candidates for explaining excess returns. Sarno and Schmeling (2014) analyze cross-sections of excess returns based on currency portfolios and find that macro fundamentals have substantial economic information content for the future behavior of exchange rates and future currency excess returns. Recent findings by Filippou and Taylor (2017) also identify common macro factors as key drivers of portfolio excess returns. Fratzscher (2009) also adopts a wide range of macroeconomic and financial factors in order to explain excess returns during the GFC. We include growth expectations, stock market returns, inflation rates, short-term interest rates and the growth rate of currency reserves and report our estimation results in Table 2.

*** Insert Table 2 about here ***

We find a strong effect of inflation on CAR for both forecast horizons. The growth of currency reserves is also significant at the 10% level over a horizon of 24 months. The remaining fundamentals turn out to be insignificant but inflation and currency reserves significantly affect the explanatory power. The R^2, without both regressors, drops from 0.41 to 0.25 for the 12-month and from 0.53 to 0.26 for the 24-month horizon. The inflation rate is linked to exchange rate movements via the conventional purchasing power parity while fluctuations in reserves could reflect actual or expected interventions by central banks to smooth exchange rate movements.

In a second step, we also regress CAR on the COVID-19 indicators relative to the US as reported in Table 3 for both major and minor currencies. For major currencies, the results are much more encouraging compared to the previous estimates based on fundamentals. The R^2 is twice as high and above 0.8 for all four configurations and both forecast horizons. All measures turn out to be highly significant. This finding is again robust to using only domestic measures, instead of relative measures compared to the US.

*** Insert Table 3 about here ***

Considering our earlier results, especially for major currencies, excess returns seem to be mostly driven by unexpected exchange rates movements, resembling forecast errors by professionals. All indicators are significant over both horizons while only two measures display significance for minor currencies. This indicates that the effect of lockdown policies on exchange rates has occurred unexpected. The picture is somehow different for minor currencies where lockdown policies had a significant effect on expectations. For CAR all measures are insignificant over the 12-month horizon while only stringency and containment health are significant over the 24-month horizon. In line with our previous line of reasoning, a potential explanation is that market participants find the effect of lockdown policies harder to predict if two large economies are involved while exchange rate movements (in times of uncertainty) seem to be easier to predict for minor currencies which are predominantly driven by US factors.

It is interesting that the policy measures display stronger effects on excess returns than established fundamentals for major currencies. This clearly shows that currency markets react stronger to policy responses during the pandemic. If we consider the exchange rate as the discounted sum of future fundamentals, policy responses seem to be considered as a useful guide for macroeconomic developments by financial markets. The weaker effect of macroeconomic fundamentals might for example be explained by the inability of short-term interest rates to reflect changes in the stance of monetary policy, such as asset purchases, which often have strong effects on exchange rates. However, appropriate measures are not available for all countries under consideration.

Finally, to underline the robustness of the findings presented in Table 3 it is worth to emphasize that we rely on a fixed effects model including country and time fixed effects. This enables us to control for all omitted factors that vary across countries but are constant over time and factors that vary over time but are constant across countries (i.e. common factors such as global shocks). Therefore, we control for unobserved heterogeneity, which otherwise might result in an omitted variables bias. In addition, the consideration of macroeconomic factors as potential determinants for CAR reported in Table 2 has shown that most macro factors are insignificant.[11] The only macro factor that is significant at the 5% level for both horizons (i.e. $h = 12$ and $h = 24$) is inflation, which is also available in a monthly frequency for most of the major economies (i.e. whose currencies are classified as major currencies). Therefore, we have re-run the fixed effects model regressions provided in Table 3 for major currencies while also controlling for inflation.[12] The additional findings are reported in Table 4 and roughly confirm the findings already presented in Table 3. Although the estimated β coefficients decrease in magnitude, they stay significantly positive in nearly all cases, especially for $h = 12$. Therefore, the findings for COVID-19 indicators do not change qualitatively. However, inflation itself, which is measured relative to the US turns out to be insignificant for $h = 12$ and significant but negative for $h = 24$.

*** Insert Table 4 about here ***

5 Conclusion

This paper studies the impact of the COVID-19 pandemic on exchange rate expectations based on survey forecasts for a large number of currencies. At the first stage, we show that the response of expectations to policy measures conducted during the pan-

[11]Macro factors have been considered in separate cross-sectional models as many of these variables are not observable on a monthly frequency (such as for example GDP growth) and/or are not available for the whole sample period for all countries. The inclusion of these factors into the fixed effects model would have otherwise strongly restricted our data set.

[12]23 of the 29 major currencies have been included in these estimations. Only the currencies of Australia, New Zealand, the Philippines, Singapore, Taiwan and Thailand have been omitted as inflation is measured either at a quarterly or at an annually frequency for these economies.

demic is unsystematic for major currencies. This finding is in line with the theoretical literature modeling imperfect information, which suggests that forecasters remain inattentive when facing noisy information (Sims, 2003). The fact that lockdown policies are conducted in two countries might result in a blurred signal and no systematic response of the corresponding expected exchange rate. In line with this reasoning, we find that forecasts are often closely attached to the current spot rate, suggesting that forecasters remain inattentive to incoming information. However, our results are remarkably different for minor currencies where US response policies have a systematic influence on the expected path of the exchange rate but are less important for forecast errors. This confirms that minor currencies are mainly driven by global factors with US policies being clearly considered the most important factor by market participants.

The second part of our analysis verifies the presence of abnormal exchange rate returns based on expectations building among professionals. We find that these returns are affected by both policy responses and macroeconomic fundamentals. Strikingly, the former has a much stronger effect on excess returns within the latest COVID-19 period, suggesting that currency markets consider lockdown policies as quite important for the future path of the economy. The potential role of expectations as a propagation mechanism for such policy shocks is complicated by the inattention of market participants. While the literature has largely focused on the effect of monetary policy on exchange rates, our findings suggest that the general policy path can affect the foreign exchange rate market substantially. Our results relate to the observed impact of fundamentals and confirm the nonlinear and unstable nature of the link between exchange rates and macroeconomic fundamentals (Sarno *et al.*, 2006; Sarno and Valente, 2009). In line with the idea of a global financial cycle, they also suggest the policymakers in very small open economies have little influence on the path of the exchange rate which is expected by market participants.

Our study also opens up points of contact for further research such as, e.g., an explicit comparison with earlier pandemic periods. Other interesting avenues for future research refer to a disaggregated analysis of expectations during the pandemic. Individual forecasts are not available within the data set under investigation in this study but could be adopted for specific currencies where such data is available. Given the established evidence for sluggish adjustment of forecasts by professionals, such data could also be used for an assessment of effects on disagreement among forecasters. An additional promising avenue for further research would be the analysis of contagion effects across foreign exchange markets during the COVID-19 pandemic. While we have considered a monthly frequency, future research could also assess the impact of news due to specific events during the pandemic on the foreign exchange market for higher frequencies, for example in terms of exchange rate volatility or effects on trading volume, in a different research setting.

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Figures and Tables

Table 1: **Regressions of expected FX change on COVID-19 indicators**

	$h = 12$				$h = 24$			
	Stringency	**Stringency Legacy**	**Government Response**	**Containment Health**	**Stringency**	**Stringency Legacy**	**Government Response**	**Containment Health**
	(a) Major currencies							
β	0.0191	0.0181	0.0276	0.0226	0.0325	0.0324	0.0504	0.0401
SE	0.0125	0.0114	0.0203	0.0181	0.0202	0.0186	0.0326	0.0295
p**-value**	0.1266	0.1157	0.1756	0.2130	0.1086	0.0824	0.1229	0.1756
Country	yes	yes	yes	yes	yes	yes	yes	yes
Time	yes	yes	yes	yes	yes	yes	yes	yes
F**-stat**	43.9666	43.8745	44.0076	43.9021	48.0781	48.0158	48.2254	48.0405
p**-value**	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.8545	0.8542	0.8546	0.8543	0.8652	0.8651	0.8656	0.8652
	(b) Minor currencies							
β	0.0098	0.0177	0.0115	0.0167	0.0080	0.0139	0.0124	0.0138
SE	0.0052	0.0053	0.0083	0.0077	0.0051	0.0053	0.0082	0.0072
p**-value**	0.0599	0.0011	0.1639	0.0298	0.1188	0.0088	0.1317	0.0558
Country	yes	yes	yes	yes	yes	yes	yes	yes
Time	yes	yes	yes	yes	yes	yes	yes	yes
F**-stat**	169.0797	171.2105	168.5519	169.8938	255.3108	257.7120	255.3985	256.4308
p**-value**	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.9609	0.9613	0.9608	0.9610	0.9737	0.9740	0.9737	0.9739

Note: The table reports estimates for β, heteroscedasticity robust standard errors (SE) and p-values for the following fixed effects regression of expected foreign exchange rate (FX) changes in percentage terms,

$$E_t(\Delta s_{i,t+h}) = \beta\text{COVID-19}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t},$$

on COVID-19 (policy) indicators relative to the US for the monthly sample period from January 2020 to December 2020. This fixed effects model including both country and time fixed effects is estimated separately for each COVID-19 policy indicator shown in each column for two forecast horizons ($h = 12$ and $h = 24$) and two groups of currencies (major currencies (Panel (a)) and minor currencies (Panel (b)). The lower parts of the table also report the F-statistic for the null $\mu_i = \lambda_t = 0$ for all i and t and the corresponding p-value. We include the following COVID-19 policy indicators: (1) the original stringency index, which records the strictness of 'lockdown style' policies, (2) a reduced version of the stringency index (i.e. the stringency legacy index), (3) an overall government response index, which records how the response of governments has varied over all indicators in the database, and (4) a containment health index, which summarizes different policy response indicators (including school closures, workplace closures, travel bans, testing policy, contact tracing, face coverings, and vaccine policy).

Table 2: **Determinants of cumulated abnormal returns for major currencies**

	$h = 12$			$h = 24$		
	β	SE	p-value	β	SE	p-value
Mean	64.0372	19.1546	0.0024	178.6557	51.6543	0.0018
Intercept	23.2303	39.3318	0.5608	70.3574	49.7142	0.1710
GDP	-2.1798	4.4326	0.6278	-3.2425	6.6913	0.6328
Stock	-0.9136	0.8791	0.3100	-0.6973	0.9752	0.4821
Reserves	-1.6649	1.0134	0.1146	-2.2971	1.1644	0.0612
Inflation	20.6043	7.6678	0.0135	41.9648	9.1235	0.0001
IR	-1.7327	6.1543	0.7809	-8.0971	9.1023	0.3833
R^2	0.4135			0.5288		

Note: The table reports OLS estimates β, heteroscedasticity robust standard errors (SE) and p-values for the following cross-sectional regression of cumulated abnormal returns (CAR),

$$\text{CAR}_i = \beta_0 + \beta_1 \text{GDP}_i + \beta_2 \text{Stock}_i + \beta_3 \text{Reserves}_i + \beta_4 \text{Inflation}_i + \beta_5 \text{IR}_i + \nu_i,$$

on GDP growth, stock returns, the growth rate of reserves, consumer price inflation and interest rates (IR) for major currencies (excluding Argentina due to data availability) for the year 2020 and for two forecast horizons ($h = 12$ and $h = 24$).

Table 3: **Regressions of cumulated abnormal returns on COVID-19 indicators**

	$h = 12$				$h = 24$			
	Stringency	**Stringency Legacy**	**Government Response**	**Containment Health**	**Stringency**	**Stringency Legacy**	**Government Response**	**Containment Health**
	(a) Major currencies							
β	0.5835	0.5394	0.9326	0.8718	1.2965	1.2257	2.0288	1.8309
SE	0.2228	0.2090	0.3146	0.2953	0.7358	0.6892	1.0573	0.9600
p**-value**	0.0093	0.0103	0.0033	0.0034	0.0791	0.0763	0.0560	0.0575
Country	yes	yes	yes	yes	yes	yes	yes	yes
Time	yes	yes	yes	yes	yes	yes	yes	yes
F**-stat**	41.2871	40.8090	42.0100	42.0923	59.8948	59.4062	60.6190	60.4841
p**-value**	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.8495	0.8480	0.8517	0.8519	0.8911	0.8903	0.8923	0.8921
	(b) Minor currencies							
β	-0.1450	-0.0013	-0.0856	-0.0716	-0.8068	-0.5804	-0.5347	-0.7126
SE	0.1170	0.1555	0.1669	0.1579	0.2885	0.3847	0.4254	0.4221
p**-value**	0.2165	0.9931	0.6087	0.6508	0.0056	0.1328	0.2101	0.0928
Country	yes	yes	yes	yes	yes	yes	yes	yes
Time	yes	yes	yes	yes	yes	yes	yes	yes
F**-stat**	18.8784	18.8144	18.8238	18.8228	34.1528	33.6432	33.4476	33.6490
p**-value**	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.7528	0.7521	0.7522	0.7522	0.8464	0.8444	0.8436	0.8444

Note: The table reports estimates for β, heteroscedasticity robust standard errors (SE) and p-values for the following fixed effects regression of cumulated abnormal returns (CAR),

$$\text{CAR}_{i,t} = \beta \text{COVID-19}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t},$$

on COVID-19 (policy) indicators relative to the US for the monthly sample period from January 2020 to December 2020. This fixed effects model including both country and time fixed effects is estimated separately for each COVID-19 policy indicator shown in each column for two forecast horizons ($h = 12$ and $h = 24$) and two groups of currencies (major currencies (Panel (a)) and minor currencies (Panel (b)). The lower parts of the table also report the F-statistic for the null $\mu_i = \lambda_t = 0$ for all i and t and the corresponding p-value. We include the following COVID-19 policy indicators: (1) the original stringency index, which records the strictness of 'lockdown style' policies, (2) a reduced version of the stringency index (i.e. the stringency legacy index), (3) an overall government response index, which records how the response of governments has varied over all indicators in the database, and (4) a containment health index, which summarizes different policy response indicators (including school closures, workplace closures, travel bans, testing policy, contact tracing, face coverings, and vaccine policy).

Table 4: **Robustness check for the regressions of cumulated abnormal returns on COVID-19 indicators**

	$h = 12$				$h = 24$			
	Stringency	**Stringency Legacy**	**Government Response**	**Containment Health**	**Stringency**	**Stringency Legacy**	**Government Response**	**Containment Health**
	(a) Major currencies							
β	0.4493	0.3771	0.8717	0.7744	0.5692	0.5599	1.3301	1.0924
SE	0.1919	0.1770	0.2725	0.2743	0.3488	0.3913	0.4923	0.4890
***p*-value**	0.0201	0.0342	0.0016	0.0052	0.1040	0.1538	0.0074	0.0264
γ	-8.1151	-8.3236	-7.9058	-7.9824	-52.2432	-52.4163	-51.7616	-51.9660
SE	6.6119	6.5415	6.5315	6.5489	16.6564	16.6228	16.4992	16.5318
***p*-value**	0.2209	0.2045	0.2273	0.2241	0.0019	0.0018	0.0019	0.0019
Country	yes	yes	yes	yes	yes	yes	yes	yes
Time	yes	yes	yes	yes	yes	yes	yes	yes
***F*-stat**	46.7643	46.3231	47.9582	47.7735	122.9121	122.7130	125.5998	124.7243
***p*-value**	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.8771	0.8760	0.8797	0.8793	0.9494	0.9493	0.9504	0.9501

Note: The table reports estimates for β and γ as well as the corresponding heteroscedasticity robust standard errors (SE) and p-values for the following fixed effects regression of cumulated abnormal returns (CAR),

$$\text{CAR}_{i,t} = \beta\text{COVID-19}_{i,t} + \gamma\text{Inflation}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t},$$

on COVID-19 (policy) indicators relative to the US and CPI inflation relative to the US for the monthly sample period from January 2020 to December 2020. Compared to Table 3, 23 of the 29 major currencies have been included in these estimation (only the currencies of Australia, New Zealand, the Philippines, Singapore, Taiwan and Thailand have been omitted as inflation is measured either at a quarterly or an annually frequency). This fixed effects model including both country and time fixed effects is estimated separately for each COVID-19 policy indicator shown in each column for two forecast horizons ($h = 12$ and $h = 24$) and two groups of currencies (major currencies (Panel (a)) and minor currencies (Panel (b)). The lower parts of the table also report the F-statistic for the null $\mu_i = \lambda_t = 0$ for all i and t and the corresponding p-value. We include the following COVID-19 policy indicators: (1) the original stringency index, which records the strictness of 'lockdown style' policies, (2) a reduced version of the stringency index (i.e. the stringency legacy index), (3) an overall government response index, which records how the response of governments has varied over all indicators in the database, and (4) a containment health index, which summarizes different policy response indicators (including school closures, workplace closures, travel bans, testing policy, contact tracing, face coverings, and vaccine policy).

Figure 1: **Aggregated cumulated abnormal returns for major currencies for** $h = 12$

The plots shows the aggregated cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for major currencies against the US dollar and a forecast horizon of $h = 12$. The pattern is illustrated for different groups of major currencies (either for all major currencies considered or for major currencies from Europe, Asia Pacific and (Latin) America, respectively). The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns.

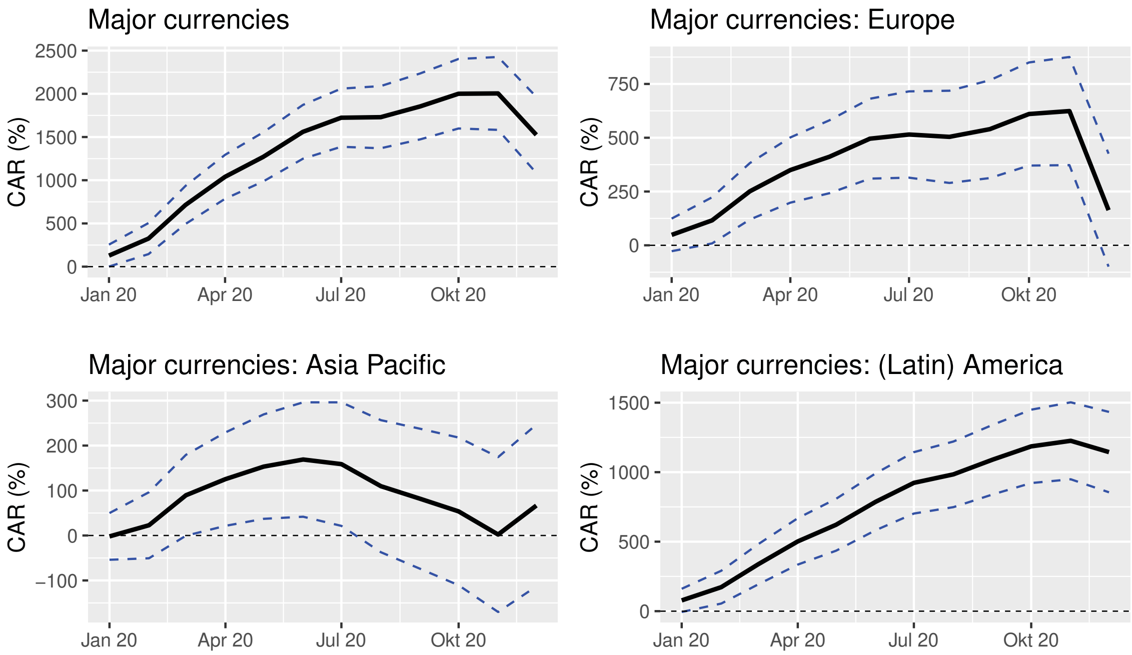


Figure 2: **Cumulated abnormal returns for major European currencies for $h = 12$**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for major European currencies against the US dollar and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

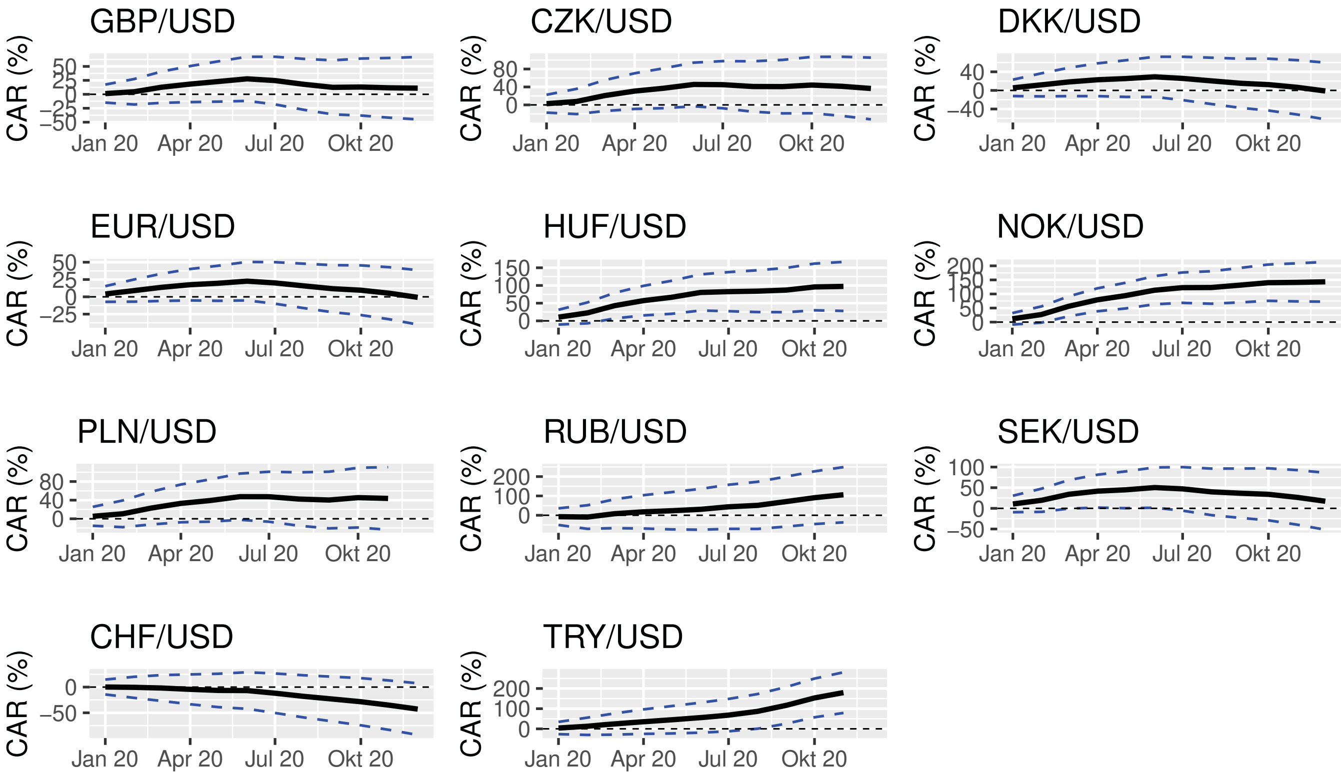


Figure 3: **Cumulated abnormal returns for major Asia Pacific currencies for $h = 12$**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for major Asia Pacific currencies against the US dollar and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

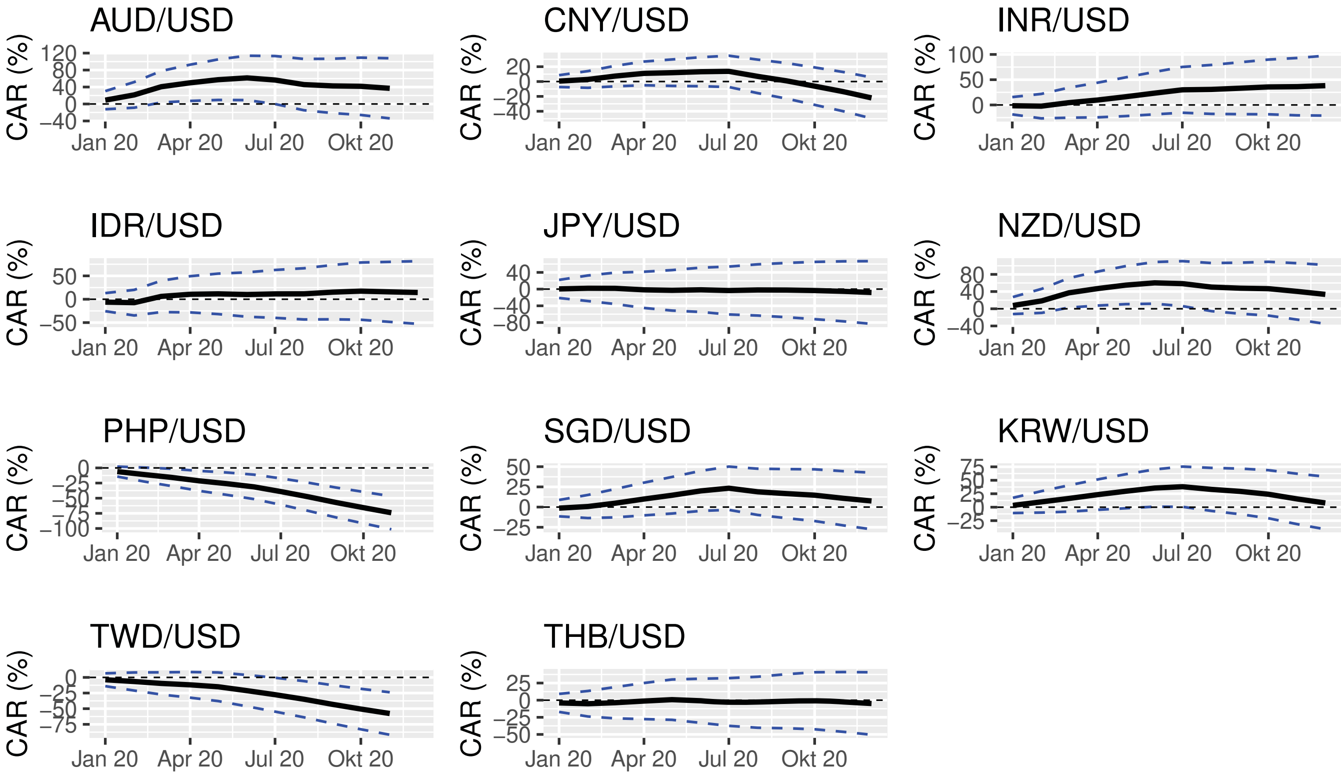


Figure 4: **Cumulated abnormal returns for major (Latin) American currencies+ for $h = 12$**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for major (Latin) American currencies against the US dollar + the South African Rand and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

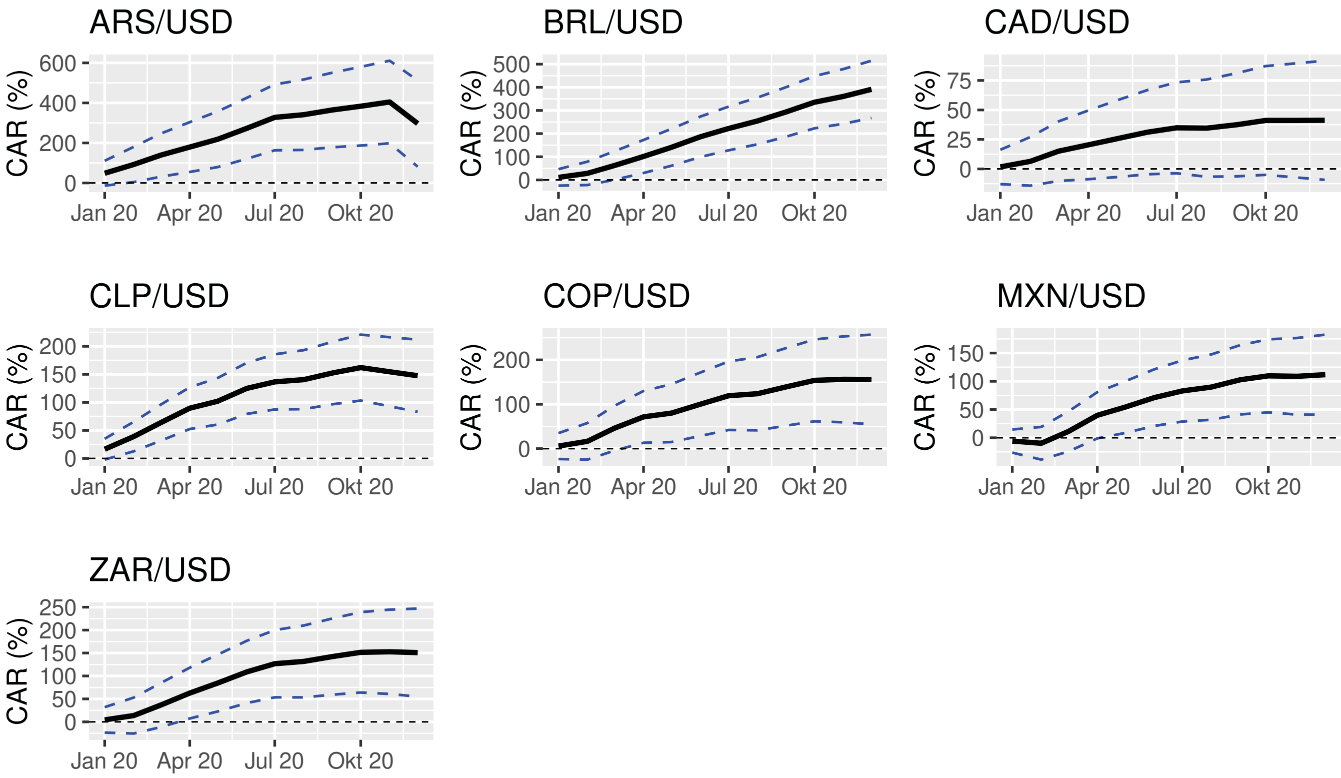


Figure 5: **Aggregated cumulated abnormal returns for major currencies for $h = 24$**

The plots shows the aggregated cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for major currencies against the US dollar and a forecast horizon of $h = 24$. The pattern is illustrated for different groups of major currencies (either for all major currencies considered or for major currencies from Europe, Asia Pacific and (Latin) America, respectively). The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns.

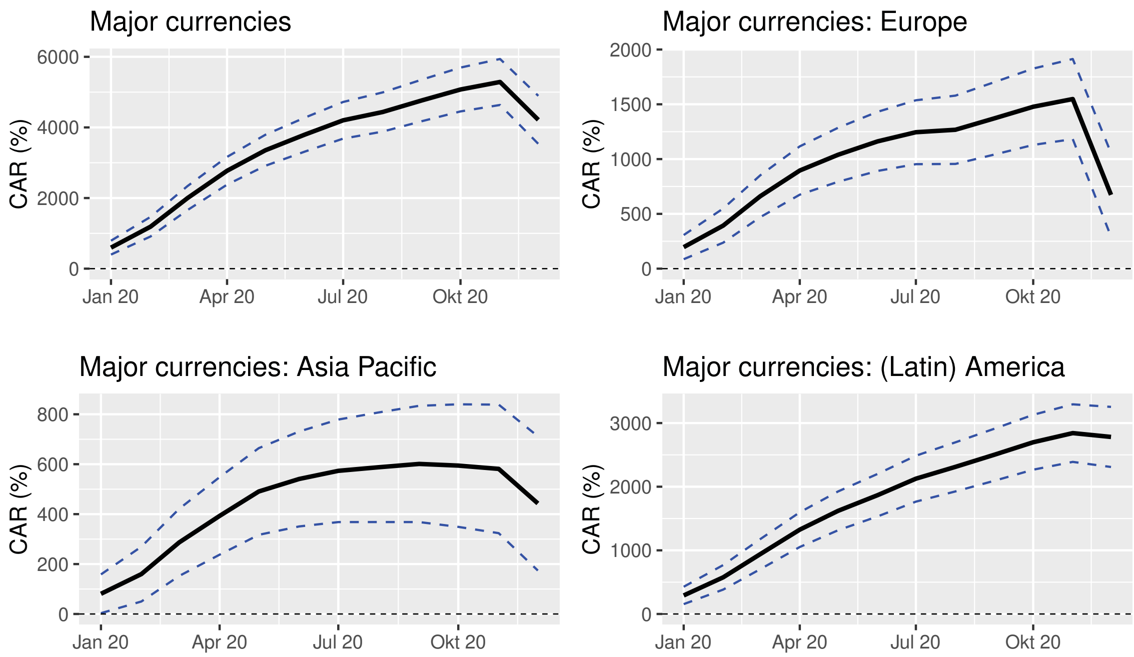


Figure 6: **Cumulated abnormal returns for major European currencies for $h = 24$**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for major European currencies against the US dollar and a forecast horizon of $h = 24$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

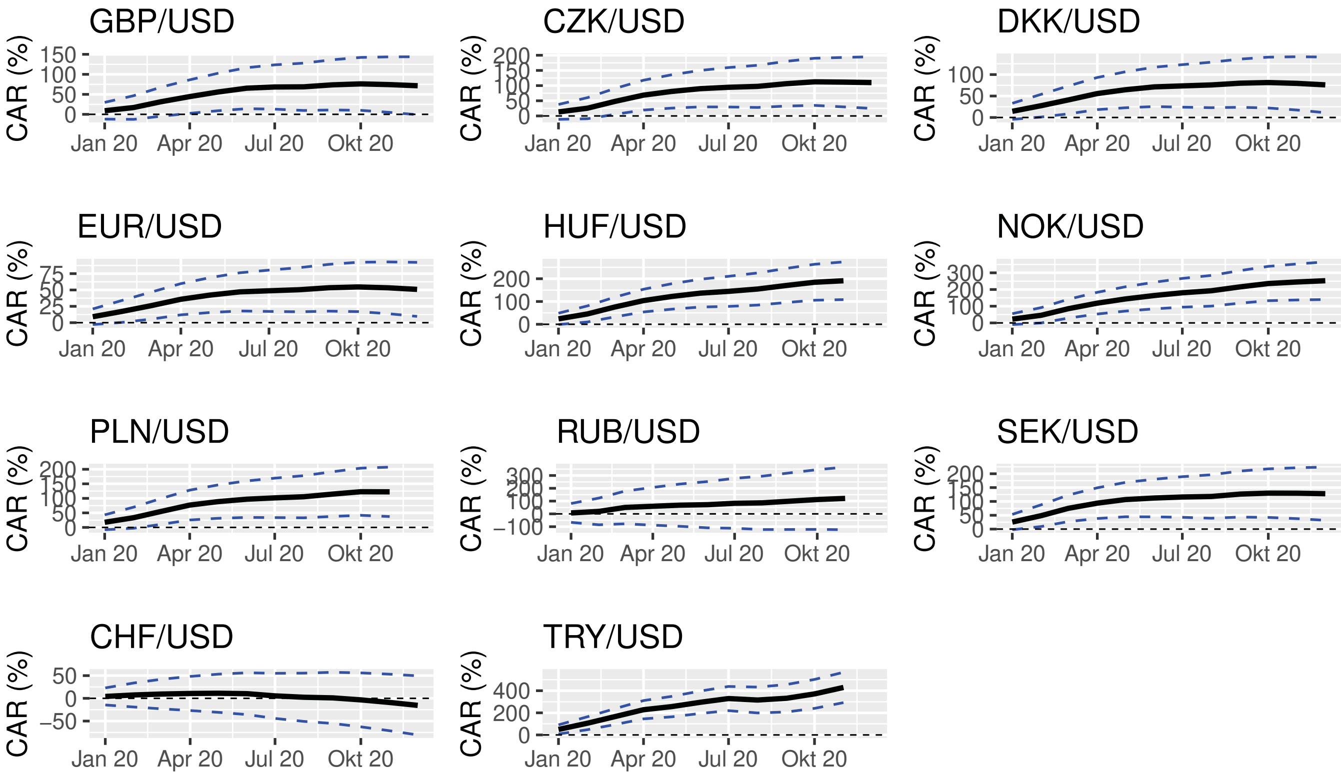


Figure 7: **Cumulated abnormal returns for major Asia Pacific currencies for $h = 24$**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for major Asia Pacific currencies against the US dollar and a forecast horizon of $h = 24$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

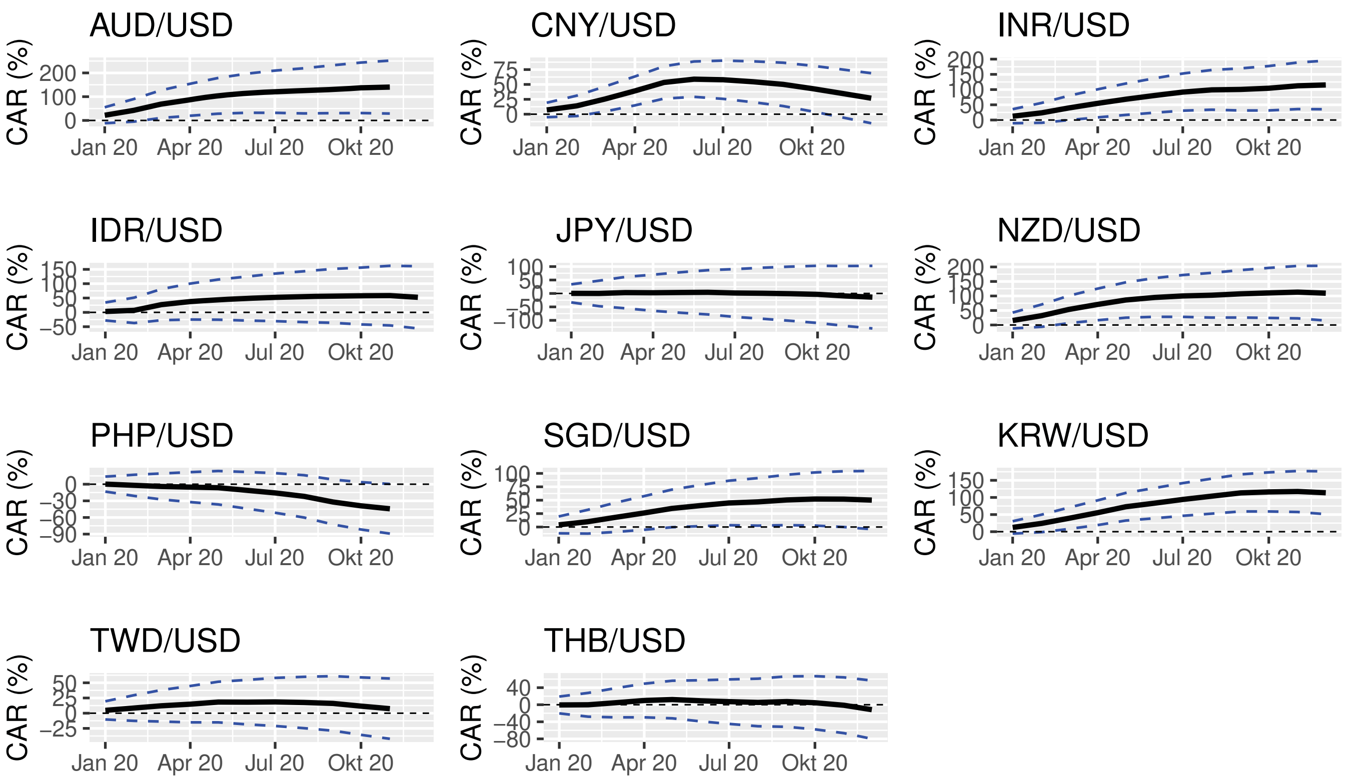


Figure 8: **Cumulated abnormal returns for major (Latin) American currencies+ for** $h = 24$

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for major (Latin) American currencies against the US dollar + the South African Rand and a forecast horizon of $h = 24$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

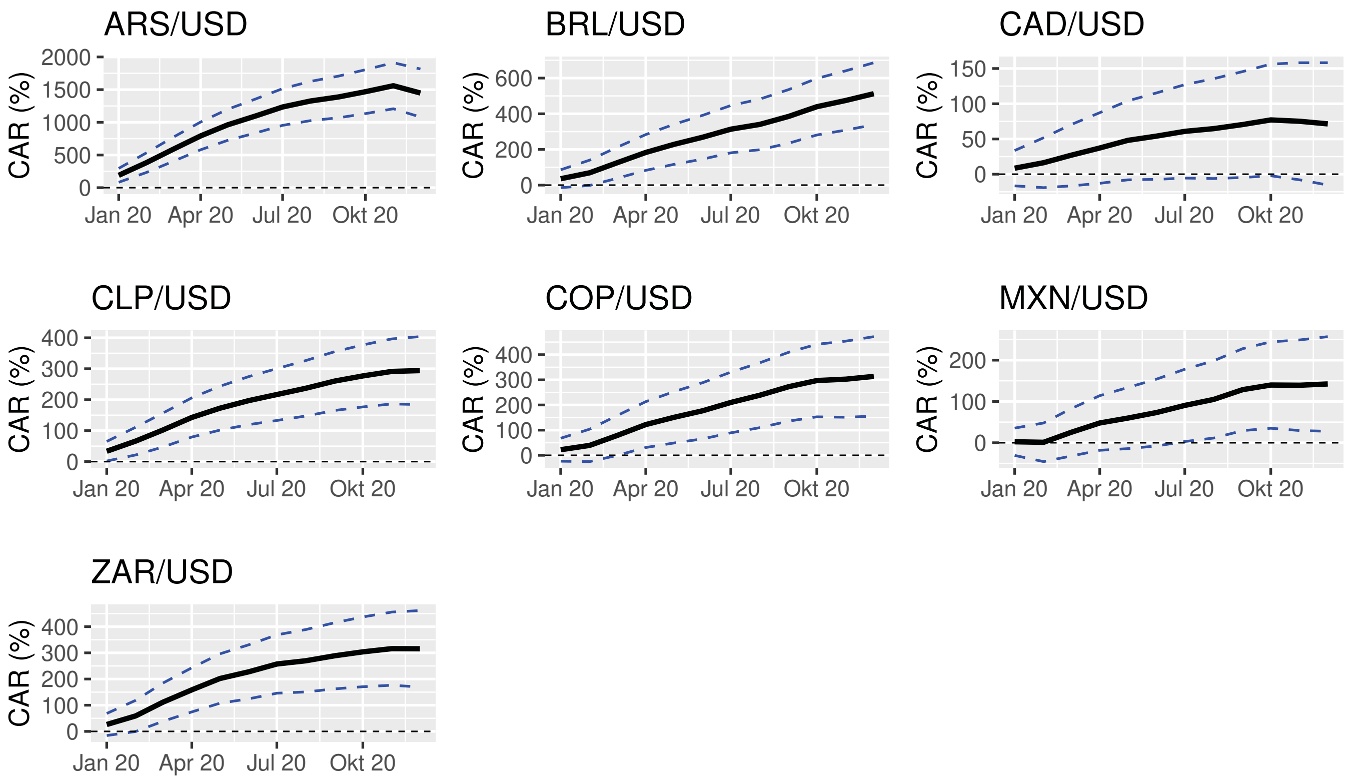
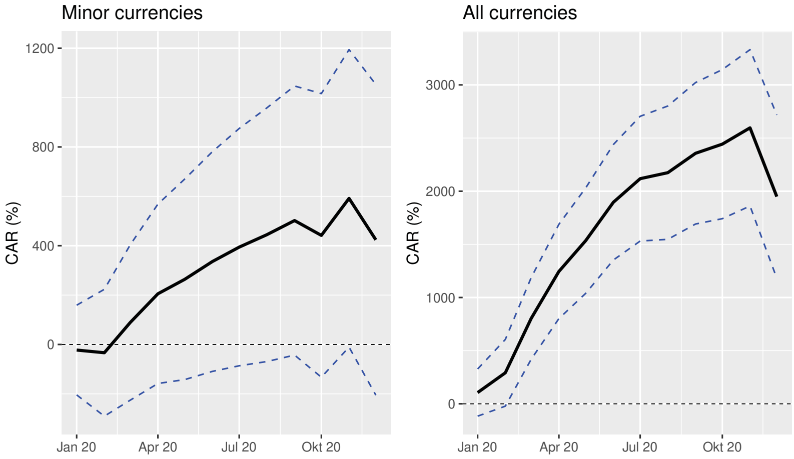


Figure 9: **Aggregated cumulated abnormal returns for minor currencies**

The plots shows the aggregated cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for minor currencies against the US dollar and all currencies including majors and minors for two forecast horizons ($h = 12$ and $h = 24$). The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns.

Panel (a): $h = 12$



Panel (b): $h = 24$

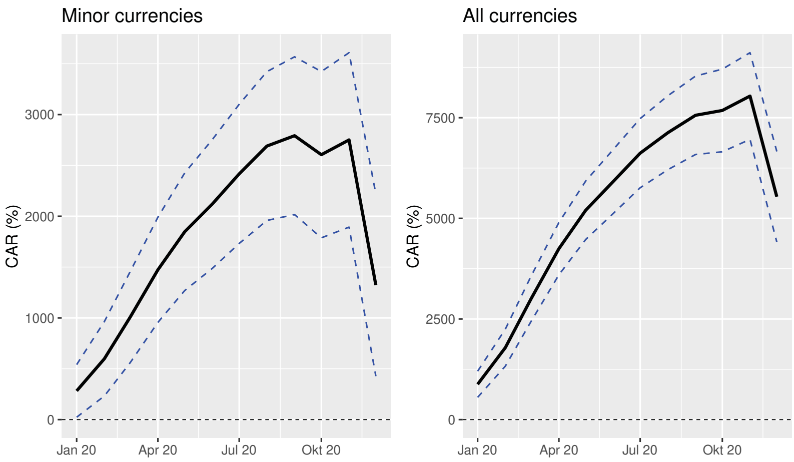


Figure 10: **Aggregated cumulated abnormal returns for major currencies for $h = 12$ during the global financial crisis period**

The plots shows the aggregated cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from July 2008 to January 2009 for major currencies against the US dollar and a forecast horizon of $h = 12$. The pattern is illustrated for different groups of major currencies (either for all major currencies considered or for major currencies from Europe, Asia Pacific and (Latin) America, respectively). The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns.

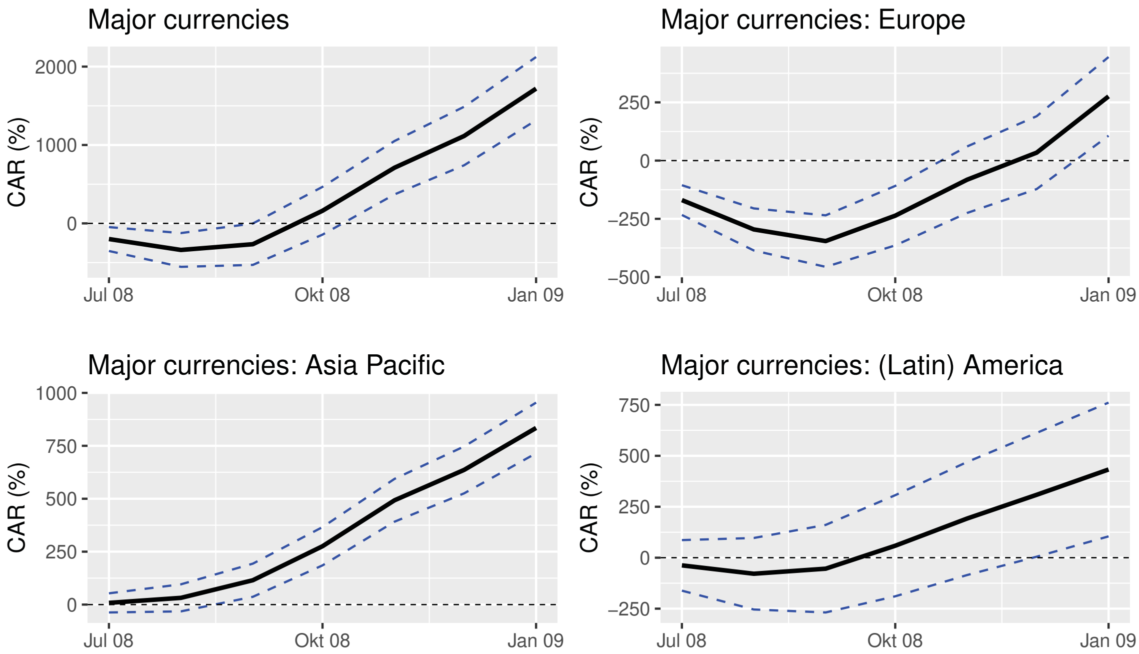


Figure 11: **Cumulated abnormal returns for major European currencies for $h = 12$ during the global financial crisis period**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from July 2008 to January 2009 for major European currencies against the US dollar and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

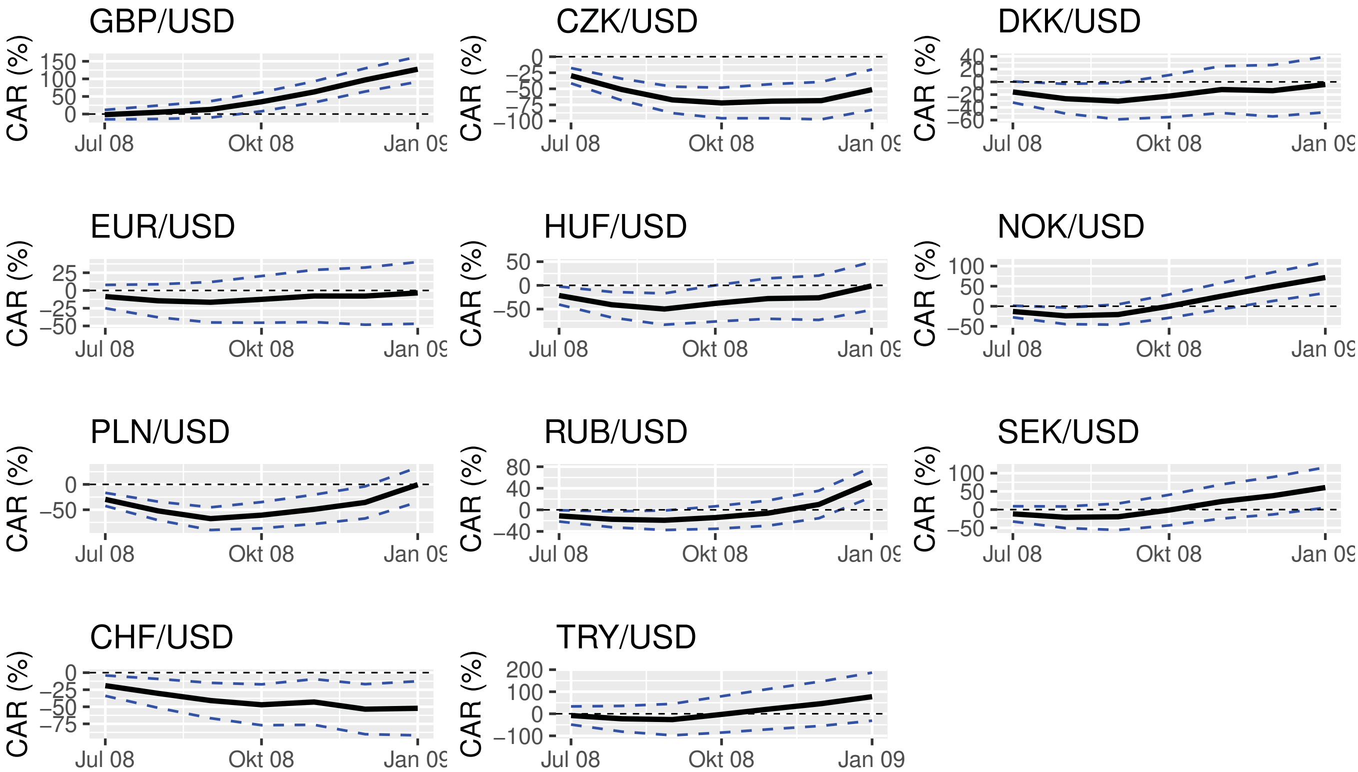


Figure 12: **Cumulated abnormal returns for major Asia Pacific currencies for $h = 12$ during the global financial crisis period**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from July 2008 to January 2009 for major Asia Pacific currencies against the US dollar and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

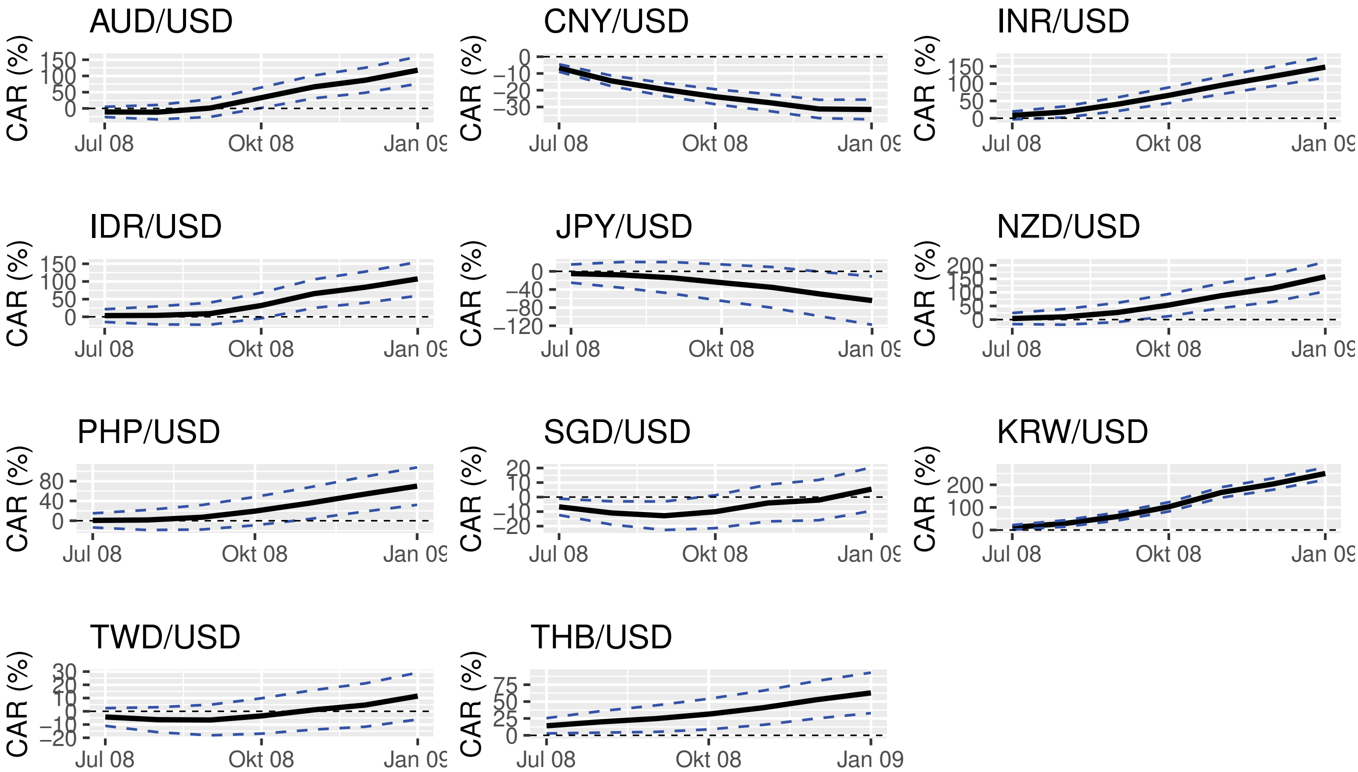


Figure 13: **Cumulated abnormal returns for major (Latin) American currencies+ for $h = 12$ during the global financial crisis period**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from July 2008 to January 2009 for major (Latin) American currencies against the US dollar + the South African Rand and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

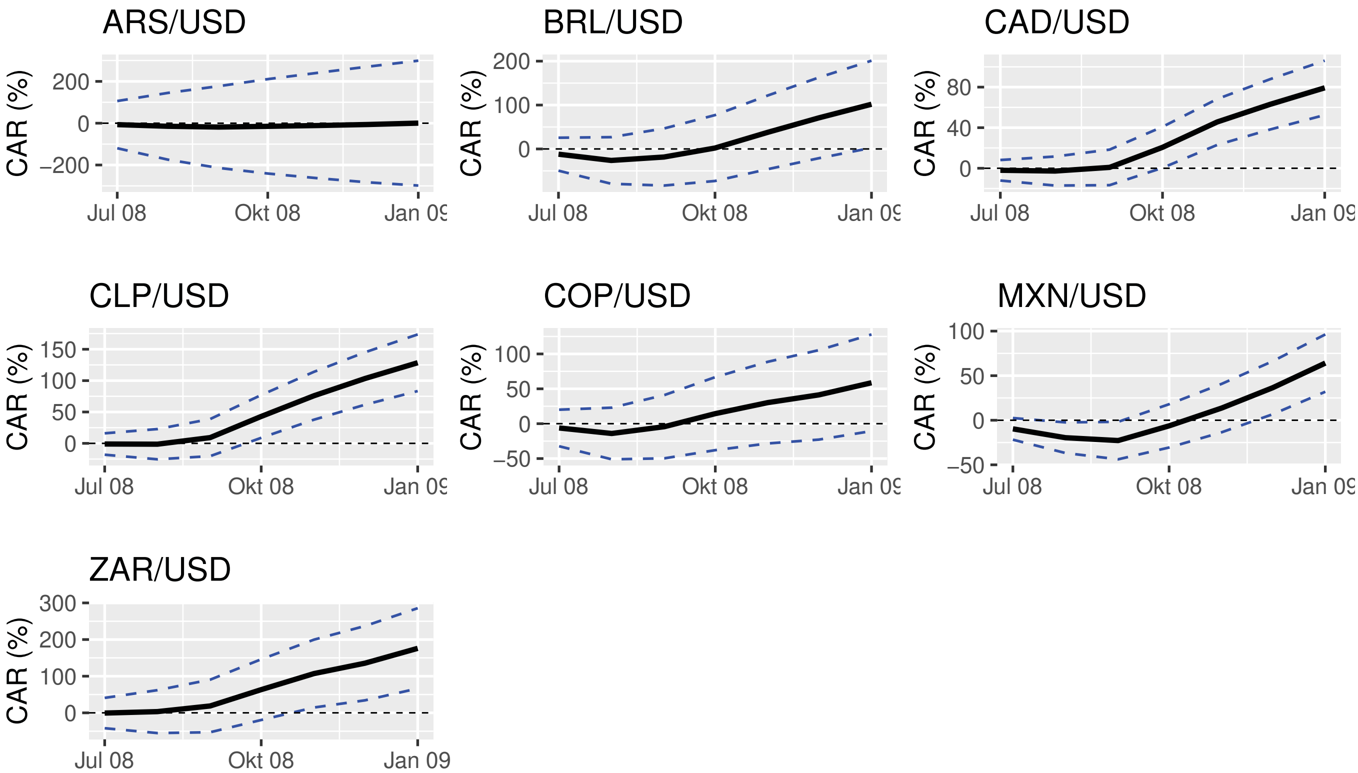
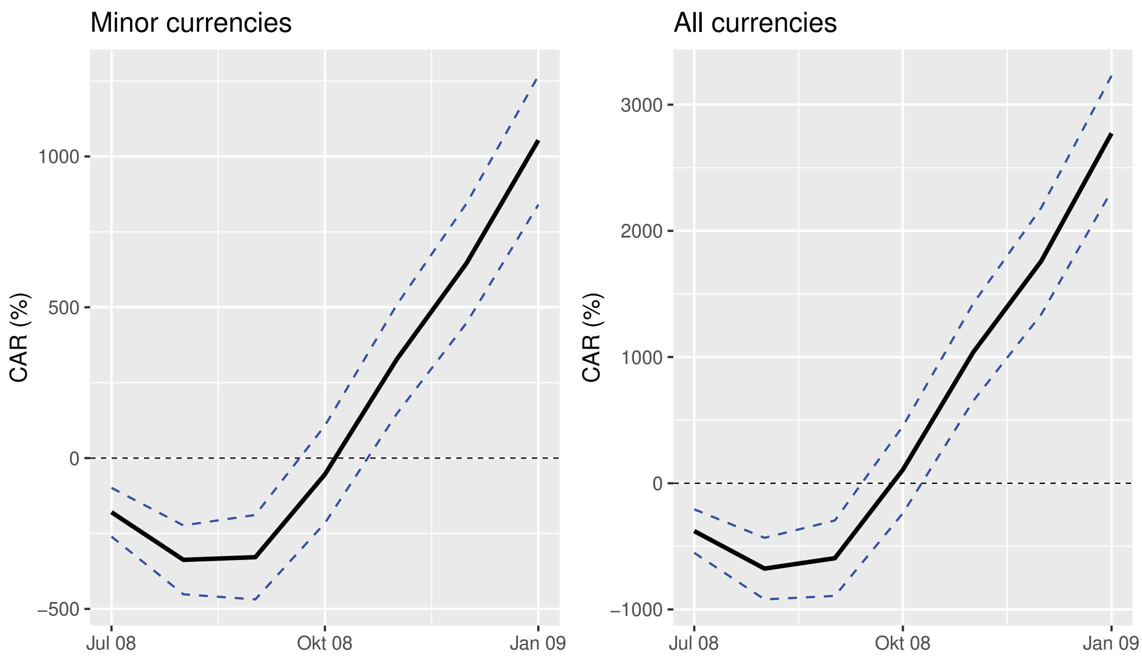


Figure 14: **Aggregated cumulated abnormal returns for minor currencies for $h = 12$ during the global financial crisis period**

The plots shows the aggregated cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from July 2008 to January 2009 for minor currencies against the US dollar and all currencies including majors and minors and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns.



Appendix

Table A.1: **Currencies within the sample**

Major currencies	**Start date**	**Minor currencies**	**Start date**
British Pound (GBP/USD)	Aug-1986	Algerian Dinar (DZD/USD)	Dec-2003
Czech Koruna (CZK/USD)	Oct-2001	Bangladeshi Taka (BDT/USD)	Dec-2003
Danish Krone (DKK/USD)	Aug-1986	Bolivian Boliviano (BOB/USD)	Dec-2003
Euro (EUR/USD)	Aug-1986	Botswana Pula (BWP/USD)	Jul-2008
Hungarian Forint (HUF/USD)	Oct-2001	Bulgarian Lev (BGN/USD)	Dec-2003
Norwegian Krone (NOK/USD)	Aug-1986	Costa Rican Colon (CRC/USD)	Feb-2006
Polish Zloty (PLN/USD)	Oct-2001	Croatian Kuna (HRK/USD)	Dec-2003
Russian Rouble (RUB/USD)	Oct-2001	Dominican Republic Peso (DOP/USD)	May-2004
Swedish Krona (SEK/USD)	Aug-1986	Egyptian Pound (EGP/USD)	Dec-2003
Swiss Franc (CHF/USD)	Aug-1986	Estonian Kroon* (EEK/USD)	Dec-2003
Turkish Lira (TRY/USD)	Oct-2001	Ghanaian Cedi (GHC/USD)	Jul-2008
Australian Dollar (AUD/USD)	Aug-1986	Icelandic Krona (ISK/USD)	Apr-2006
Chinese Renminbi (CNY/USD)	Oct-2001	Israeli Shekel (ILS/USD)	Dec-2003
Indian Rupee (INR/USD)	Oct-2001	Ivory Coast Franc (XOF/USD)	Jul-2008
Indonesian Rupiah (IDR/USD)	Oct-2001	Jamaican Dollar (JMP/USD)	Feb-2004
Japanese Yen (JPY/USD)	Aug-1986	Kazakhstan Tenge (KZT/USD)	Feb-2006
New Zealand Dollar (NZD/USD)	Aug-1986	Kenyan Shilling (KES/USD)	Dec-2003
Philippine Peso (PHP/USD)	Oct-2001	Latvian Lat* (LVL/USD)	Dec-2003
Singapore Dollar (SGD/USD)	Oct-2001	Lebanese Pound (LBP/USD)	Jul-2008
South Korean Won (KRW/USD)	Oct-2001	Lithuanian Lita* (LTL/USD)	Dec-2003
Taiwan Dollar (TWD/USD)	Oct-2001	Malaysian Ringgit (MYR/USD)	Jan-2004
Thai Baht (THB/USD)	Oct-2001	Moroccan Dirham (MAD/USD)	Dec-2003
Argentine Peso (ARS/USD)	Oct-2001	Nigerian Naira (NGN/USD)	Dec-2003
Brazilian Real (BRL/USD)	Oct-2001	Pakistani Rupee (PKR/USD)	Dec-2003
Canadian Dollar (CAD/USD)	Aug-1986	Paraguayan Guarani (PYG/USD)	Dec-2003
Chilean Peso (CLP/USD)	Oct-2001	Peruvian Peso (PEN/USD)	Jan-2004
Colombian Peso (COP/USD)	Oct-2001	Romanian Leu (RON/USD)	Dec-2003
Mexican Peso (MXN/USD)	Oct-2001	Serbian Dinar (RSD/USD)	Aug-2004
South African Rand (ZAR/USD)	Oct-2001	Sri Lankan Rupee (LKR/USD)	Jul-2008
		Tanzanian Shilling (TZS/USD)	Feb-2006
		Trinidad & Tobago Dollar (TTD/USD)	May-2005
		Ugandan Shilling (UGX/USD)	Jul-2008
		Ukrainian Hryvnia (UAH/USD)	Dec-2003
		Uruguayan Peso (UYU/USD)	Dec-2003
		Vietnamese Dong (VND/USD)	Dec-2003
		Zambian Kwacha (ZMK/USD)	Jul-2008

Note: The table reports all currencies included within the data set provided by FX4casts. We have excluded the Venezuelan Bolivar due to its extreme depreciation and also a few minor currencies that have been constant throughout (nearly) the entire sample period. The start date refers to the date when FX4casts started to collect 12-month forecasts. 24-month forecasts are only available since Jul-2008 for all currencies. *The currencies of the three Baltic countries (Estonian Kroon, Latvian Lat and Lithuanian Lita) are discontinued from the period the countries joined the Euro Area and are therefore not included within the study of the COVID-19 effect but only in the accompanying study on the effect of the global financial crisis.

Table A.2: **Normality tests for abnormal returns of major currencies**

	$h = 12$				$h = 24$			
	Mean	**p-value**	**JB-stat**	**p-value**	**Mean**	**p-value**	**JB-stat**	**p-value**
GBP/USD	1.2528	0.5097	0.0603	0.9703	3.7203	0.2706	6.2698	0.0435
CZK/USD	-0.6734	0.7607	2.5084	0.2853	1.1622	0.7954	4.4626	0.1074
DKK/USD	0.1276	0.9288	3.0642	0.2161	1.8876	0.5193	5.0958	0.0782
EUR/USD	-0.4143	0.6818	2.4682	0.2911	0.5235	0.7753	4.3336	0.1145
HUF/USD	1.1033	0.5702	2.8551	0.2399	5.1971	0.1198	1.5558	0.4594
NOK/USD	5.0530	0.0901	5.2029	0.0742	9.7853	0.0606	4.6005	0.1002
PLN/USD	-0.3815	0.8688	1.4224	0.4910	2.8692	0.3986	0.6994	0.7049
RUB/USD	5.9467	0.3424	99.3104	0.0000	18.7044	0.0509	26.7742	0.0000
SEK/USD	3.6262	0.1455	0.5726	0.7510	6.8795	0.1694	0.0821	0.9598
CHF/USD	-3.1631	0.1001	28.2588	0.0000	-4.4321	0.2190	26.5241	0.0000
TRY/USD	10.3739	0.0026	76.1814	0.0000	26.8921	0.0006	23.0242	0.0000
AUD/USD	0.3066	0.9283	2.4733	0.2904	3.4663	0.5169	3.9129	0.1414
CNY/USD	0.4683	0.5643	36.5359	0.0000	1.4140	0.4568	1.7218	0.4228
INR/USD	5.1300	0.0394	5.2752	0.0715	11.2774	0.0091	2.0623	0.3566
IDR/USD	4.0345	0.2417	0.0073	0.9964	10.4148	0.0031	0.6132	0.7360
JPY/USD	-1.2985	0.6752	5.4829	0.0645	0.1174	0.9795	7.1742	0.0277
NZD/USD	-1.4829	0.5764	4.6077	0.0999	-0.4493	0.9296	1.1507	0.5625
PHP/USD	1.5790	0.1500	1.0928	0.5790	4.4847	0.1437	13.6175	0.0011
SGD/USD	-0.0953	0.9514	2.7756	0.2496	0.7960	0.7836	1.5113	0.4697
KRW/USD	0.1145	0.9457	21.8823	0.0000	1.2345	0.6060	15.8554	0.0004
TWD/USD	0.0912	0.9515	9.1385	0.0104	0.7530	0.7319	3.3682	0.1856
THB/USD	-1.3558	0.5377	4.9318	0.0849	-1.2951	0.6997	5.1371	0.0766
ARS/USD	19.7625	0.0485	43.5884	0.0000	49.6864	0.0000	103.7468	0.0000
BRL/USD	7.7241	0.0778	12.9957	0.0015	18.7526	0.0164	0.4959	0.7804
CAD/USD	2.0710	0.3865	6.0058	0.0496	5.3068	0.2779	0.0878	0.9570
CLP/USD	2.2449	0.4631	5.0029	0.0820	6.5778	0.2167	0.9735	0.6146
COP/USD	4.9751	0.2445	51.5926	0.0000	12.3689	0.1031	13.8033	0.0010
MXN/USD	5.2517	0.1199	5.7961	0.0551	12.5450	0.0333	8.4736	0.0145
ZAR/USD	3.1067	0.4408	3.0209	0.2208	9.5992	0.2251	6.2655	0.0436

Note: The table reports the means for the abnormal returns $AR_{i,t,12}$ computed for the estimation window from January 2010 to December 2019 together with p-values for testing whether the means are equal to zero, the Jarque–Bera (JB) test statistic for testing the null of normality of $AR_{i,t,12}$ for the estimation window and its p-values. All statistics are reported for two forecast horizons ($h = 12$ and $h = 24$). See Table A.1 for the currencies codes.

Table A.3: **Normality tests for abnormal returns of minor currencies**

	$h = 12$				$h = 24$			
	Mean	p**-value**	**JB-stat**	p**-value**	**Mean**	p**-value**	**JB-stat**	p**-value**
DZD/USD	2.1940	0.1684	61.2224	0.0000	7.9169	0.0022	15.0305	0.0005
BDT/USD	0.3109	0.7340	23.3318	0.0000	2.2611	0.1274	19.5059	0.0001
BOB/USD	-0.3869	0.2374	1.2520	0.5347	-0.3233	0.6444	5.7019	0.0578
BWP/USD	0.0071	0.9974	1.8103	0.4045	2.2386	0.6369	8.7357	0.0127
BGN/USD	-0.5197	0.7772	3.1751	0.2044	0.7162	0.8157	5.7252	0.0571
CRC/USD	-0.5022	0.7645	5.9306	0.0515	0.2380	0.9454	17.9656	0.0001
HRK/USD	-0.4033	0.8358	4.1209	0.1274	1.2468	0.6933	4.8634	0.0879
DOP/USD	0.7896	0.0703	53.4084	0.0000	3.2851	0.0007	3.4015	0.1825
EGP/USD	11.0713	0.1947	264.8599	0.0000	28.8248	0.0738	41.8982	0.0000
GHC/USD	5.1964	0.1137	8.9221	0.0116	19.4698	0.0216	22.4625	0.0000
ISK/USD	-2.7049	0.2181	6.0529	0.0485	-3.7314	0.2985	6.9721	0.0306
ILS/USD	-1.7257	0.0839	8.6806	0.0130	-2.1915	0.2181	4.6384	0.0984
JMP/USD	1.4093	0.4149	2.6638	0.2640	5.1268	0.0654	5.3128	0.0702
KZT/USD	8.8006	0.1170	190.6094	0.0000	21.6095	0.0240	27.4482	0.0000
KES/USD	-1.0610	0.2440	5.3876	0.0676	-0.1033	0.9631	0.4591	0.7949
LBP/USD	-1.4561	0.0000	4347.1853	0.0000	-2.1295	0.0000	171.3003	0.0000
MYR/USD	1.5216	0.5613	21.1978	0.0000	3.9508	0.4185	1.7794	0.4108
MAD/USD	0.4852	0.7382	7.0643	0.0292	0.8542	0.7851	8.7916	0.0123
NGN/USD	-0.2878	0.9521	75.5694	0.0000	10.0952	0.2208	26.0660	0.0000
PKR/USD	2.8258	0.3132	45.6640	0.0000	6.3141	0.0158	57.0547	0.0000
PYG/USD	0.7634	0.7059	5.1122	0.0776	3.0171	0.4516	4.6080	0.0999
PEN/USD	0.1973	0.9151	0.9266	0.6292	0.8542	0.7747	1.3879	0.4996
RON/USD	0.8354	0.5911	4.4144	0.1100	3.9706	0.1473	3.6494	0.1613
RSD/USD	1.1172	0.6344	5.8290	0.0542	3.8964	0.4329	2.9940	0.2238
LKR/USD	2.6429	0.0002	28.5271	0.0000	6.6474	0.0000	5.9675	0.0506
TZS/USD	-0.0149	0.9915	26.3672	0.0000	4.7151	0.0587	2.9586	0.2278
TTD/USD	0.2007	0.7205	3.3934	0.1833	0.3714	0.7019	3.1618	0.2058
UGX/USD	0.3164	0.8580	17.1596	0.0002	5.0025	0.2207	2.3405	0.3103
UAH/USD	9.1213	0.3760	774.8526	0.0000	31.2326	0.1042	49.3594	0.0000
UYU/USD	2.4829	0.4438	6.4648	0.0395	6.3362	0.3621	43.6979	0.0000
VND/USD	0.1871	0.8224	3.1201	0.2101	2.2215	0.1877	4.4879	0.1060
ZMK/USD	-36.7348	0.1599	10.9548	0.0042	-39.3444	0.1670	10.2969	0.0058

Note: The table reports the means for the abnormal returns $AR_{i,t,12}$ computed for the estimation window from January 2010 to December 2019 together with p-values for testing whether the means are equal to zero, the Jarque–Bera (JB) test statistic for testing the null of normality of $AR_{i,t,12}$ for the estimation window and its p-values. All statistics are reported for two forecast horizons ($h = 12$ and $h = 24$). See Table A.1 for the currencies codes.

Table A.4: **Correlation between spot rate and expectations**

Major currencies	$h=12$	$h=24$	Minor currencies	$h=12$	$h=24$
GBP/USD	0.9789	0.9656	**DZD/USD**	0.9923	0.9788
CZK/USD	0.9603	0.9505	**BDT/USD**	0.9405	0.8711
DKK/USD	0.9415	0.9272	**BOB/USD**	0.3490	0.2155
EUR/USD	0.9441	0.9269	**BWP/USD**	0.9845	0.9608
HUF/USD	0.9763	0.9742	**BGN/USD**	0.9593	0.9480
NOK/USD	0.9903	0.9879	**CRC/USD**	0.9754	0.9461
PLN/USD	0.9601	0.9561	**HRK/USD**	0.9639	0.9504
RUB/USD	0.9976	0.9953	**DOP/USD**	0.9940	0.9902
SEK/USD	0.9841	0.9804	**EGP/USD**	0.9973	0.9982
CHF/USD	0.8534	0.7813	**GHC/USD**	0.9967	0.9927
TRY/USD	0.9990	0.9978	**ISK/USD**	0.9755	0.9507
AUD/USD	0.9812	0.9775	**ILS/USD**	0.9626	0.9467
CNY/USD	0.9236	0.8900	**XOF/USD**	0.9580	0.9082
INR/USD	0.9935	0.9885	**JMP/USD**	0.9852	0.9706
IDR/USD	0.9927	0.9895	**KZT/USD**	0.9977	0.9967
JPY/USD	0.9779	0.9609	**KES/USD**	0.9693	0.9228
NZD/USD	0.9563	0.9403	**LBP/USD**	0.5118	-0.1129
PHP/USD	0.9702	0.9654	**MYR/USD**	0.9849	0.9725
SGD/USD	0.9420	0.9296	**MAD/USD**	0.9504	0.9104
KRW/USD	0.8534	0.8162	**NGN/USD**	0.9977	0.9954
TWD/USD	0.9313	0.8936	**PKR/USD**	0.9970	0.9938
THB/USD	0.9637	0.9268	**PYG/USD**	0.9810	0.9652
ARS/USD	0.9916	0.9835	**PEN/USD**	0.9647	0.9168
BRL/USD	0.9951	0.9902	**RON/USD**	0.9770	0.9696
CAD/USD	0.9842	0.9811	**RSD/USD**	0.9712	0.9469
CLP/USD	0.9879	0.9858	**LKR/USD**	0.9939	0.9821
COP/USD	0.9950	0.9939	**TZS/USD**	0.9784	0.9498
MXN/USD	0.9941	0.9893	**TTD/USD**	0.8503	0.6690
ZAR/USD	0.9949	0.9937	**UGX/USD**	0.9772	0.9555
			UAH/USD	0.9936	0.9843
			UYU/USD	0.9923	0.9544
			VND/USD	0.9513	0.8887
			ZMK/USD	0.9995	0.9990

Note: The table reports the correlation coefficient between the current foreign exchange spot rate at the moment expectations are made and its $h = 12$- and $h = 24$-period forecast for the sample period from January 2010 to December 2020. See Table A.1 for the currencies codes.

Figure A.1: **Cumulated abnormal returns for minor currencies part I for $h = 12$**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for minor currencies against the US dollar and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

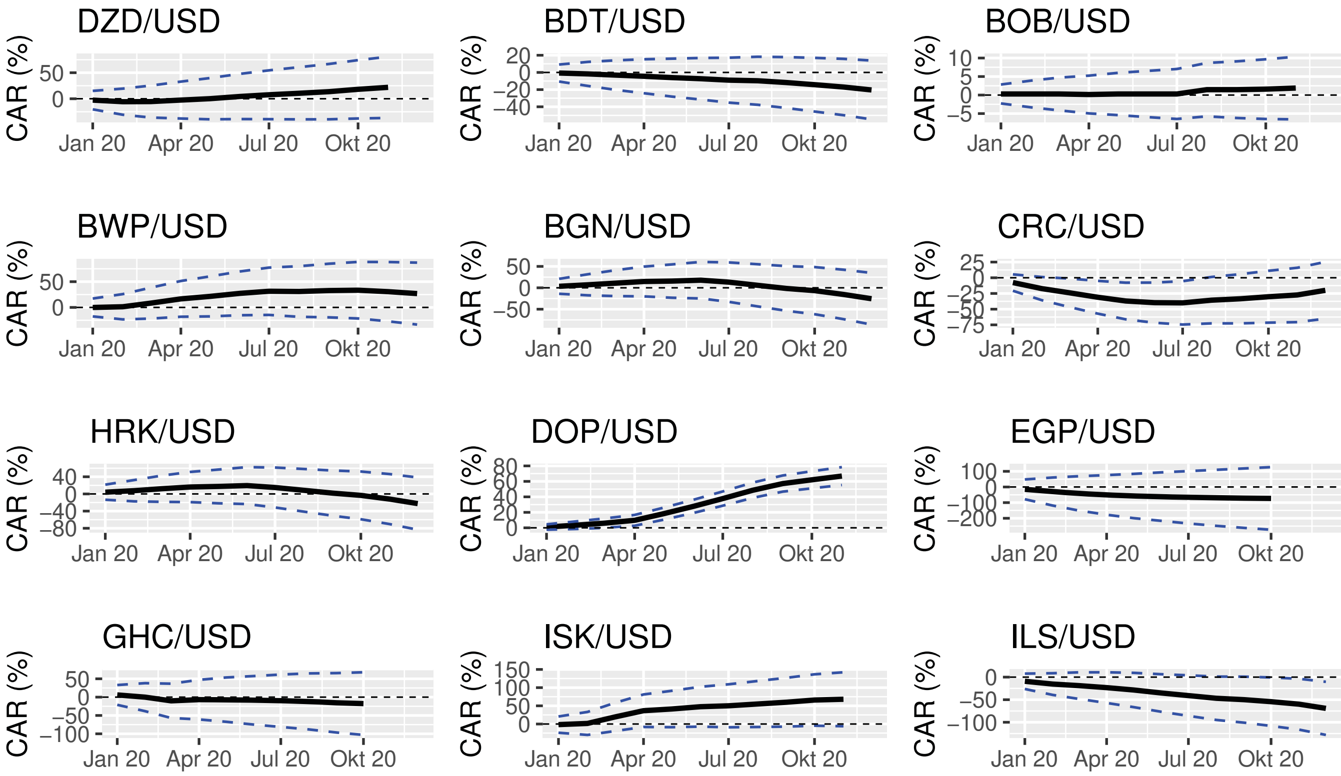


Figure A.2: **Cumulated abnormal returns for minor currencies part II for $h = 12$**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for minor currencies against the US dollar and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

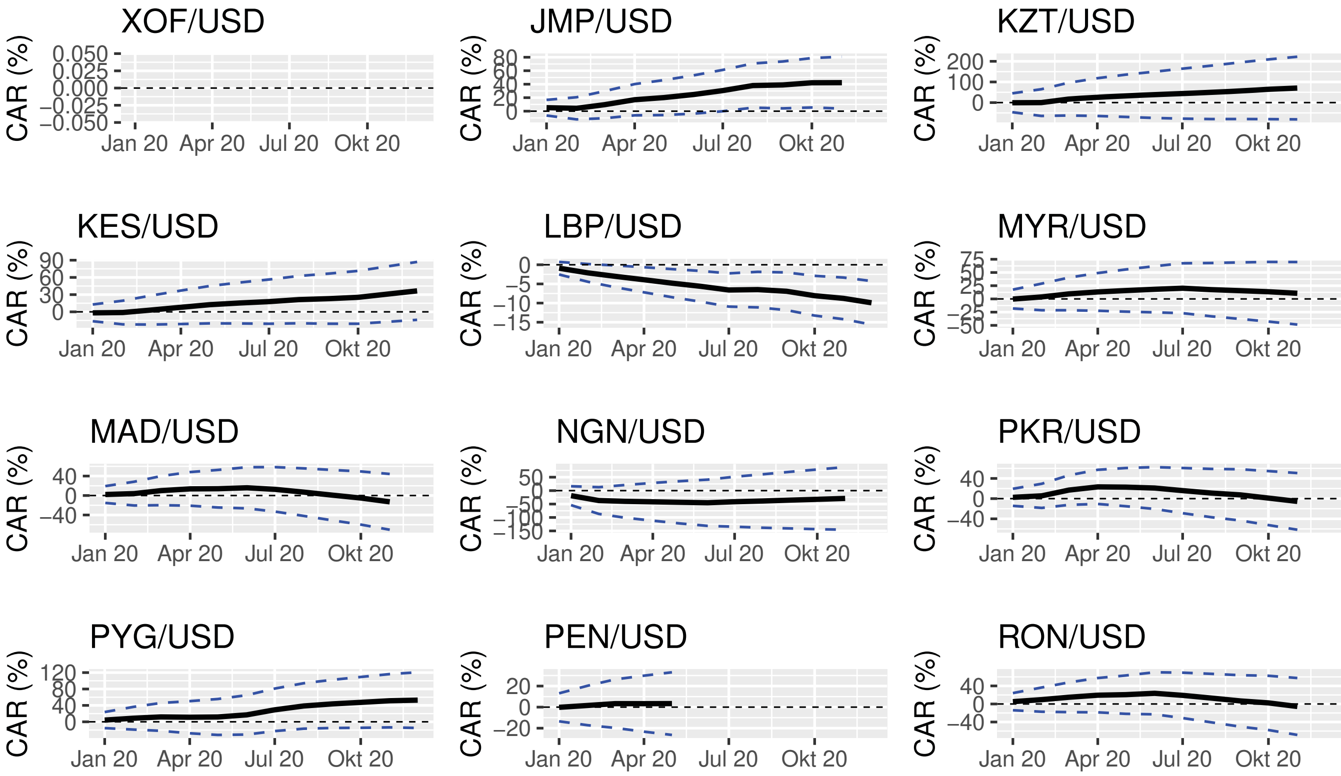


Figure A.3: **Cumulated abnormal returns for minor currencies part III for $h = 12$**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for minor currencies against the US dollar and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

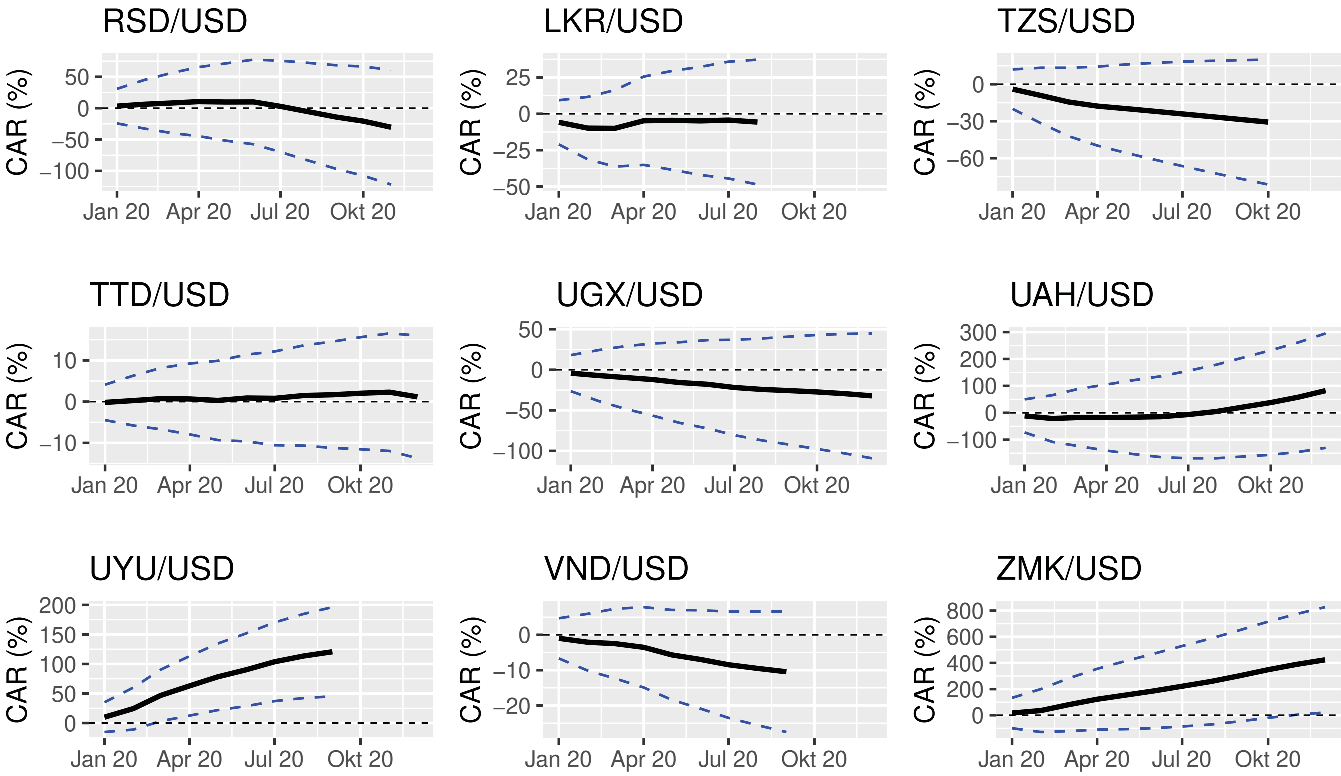


Figure A.4: **Cumulated abnormal returns for minor currencies part I for $h = 24$**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for minor currencies against the US dollar and a forecast horizon of $h = 24$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

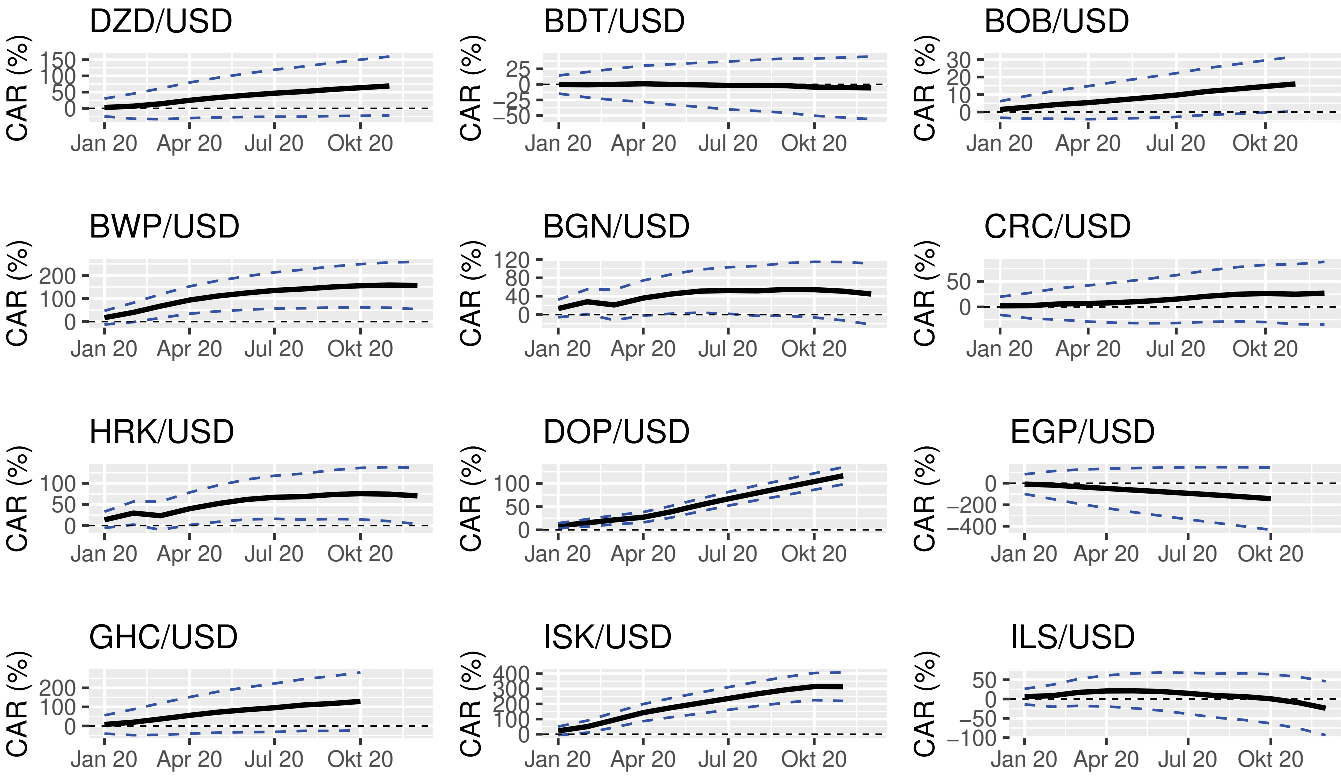


Figure A.5: **Cumulated abnormal returns for minor currencies part II for $h = 24$**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for minor currencies against the US dollar and a forecast horizon of $h = 24$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

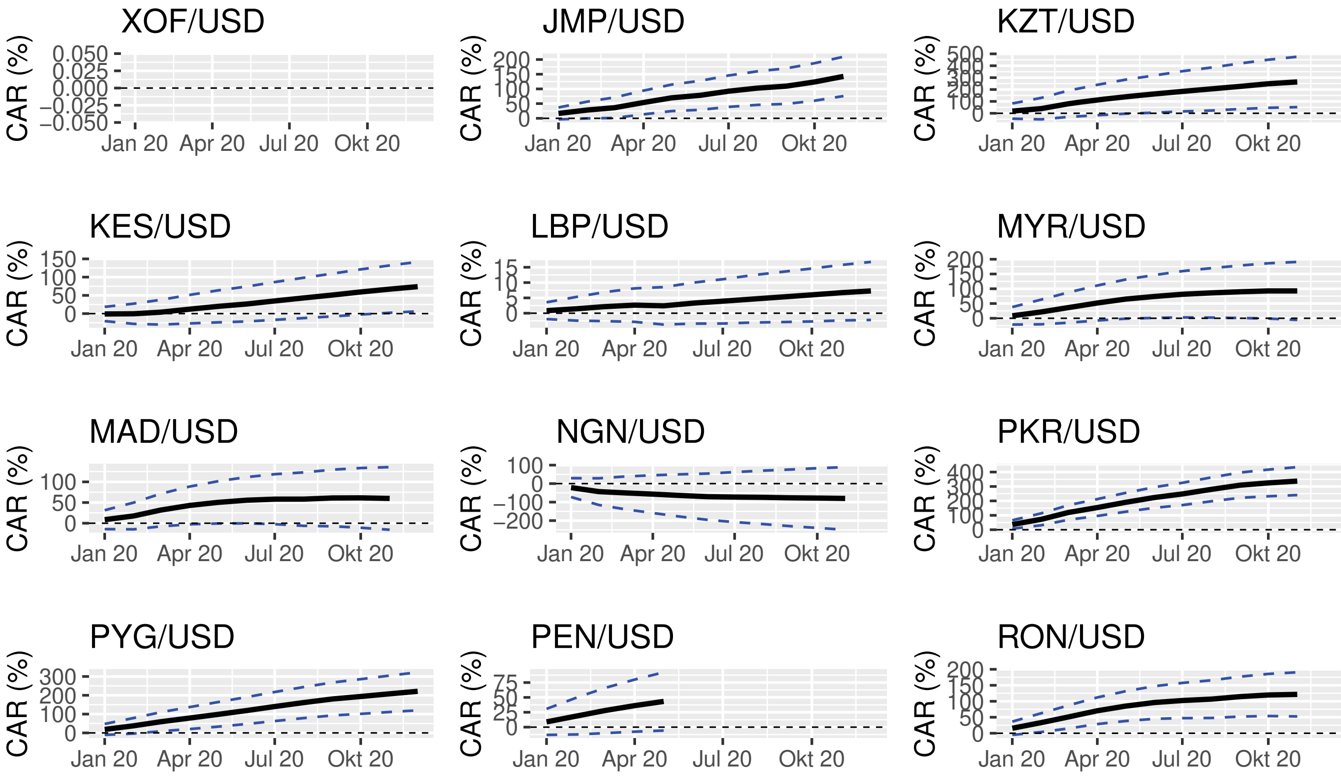


Figure A.6: **Cumulated abnormal returns for minor currencies part III for $h = 24$**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from January 2020 to December 2020 for minor currencies against the US dollar and a forecast horizon of $h = 24$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

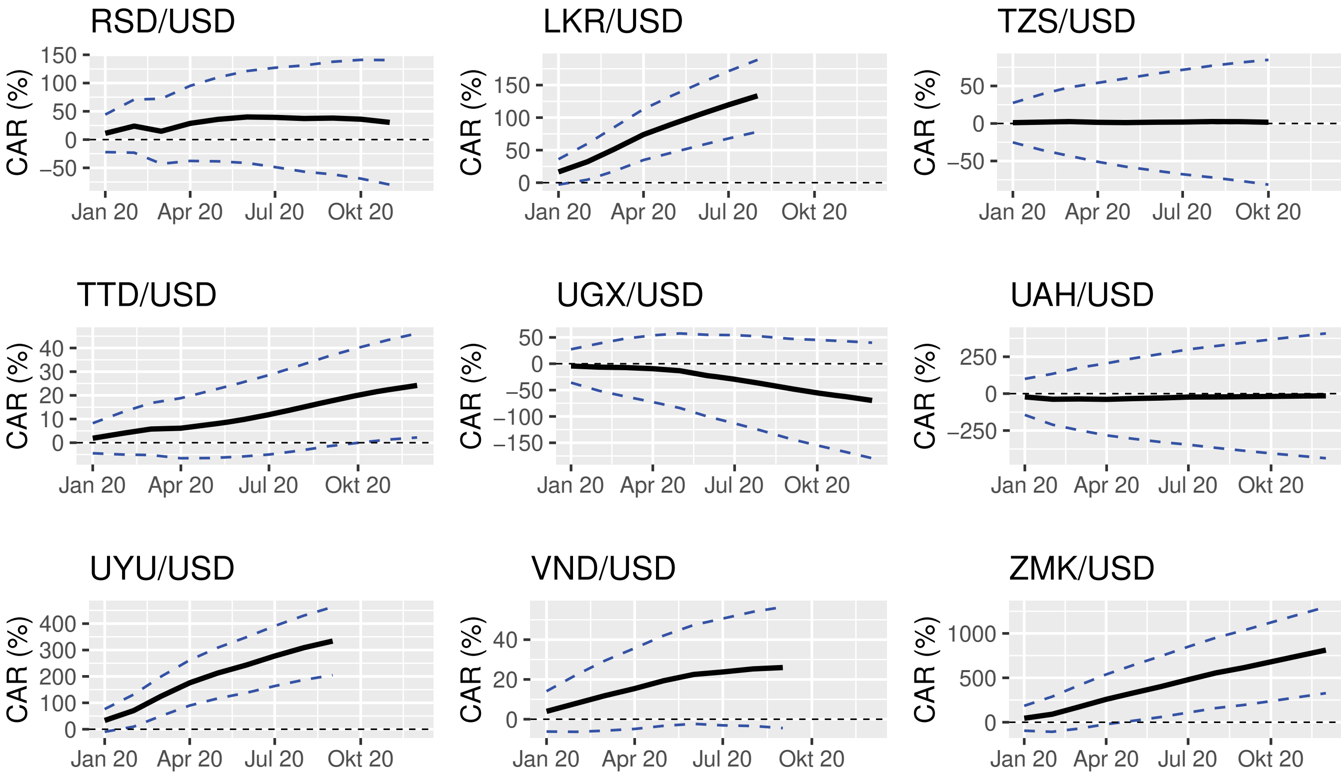


Figure A.7: **Cumulated abnormal returns for minor currencies part I for $h = 12$ during the global financial crisis period**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from July 2008 to January 2009 for minor currencies against the US dollar and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

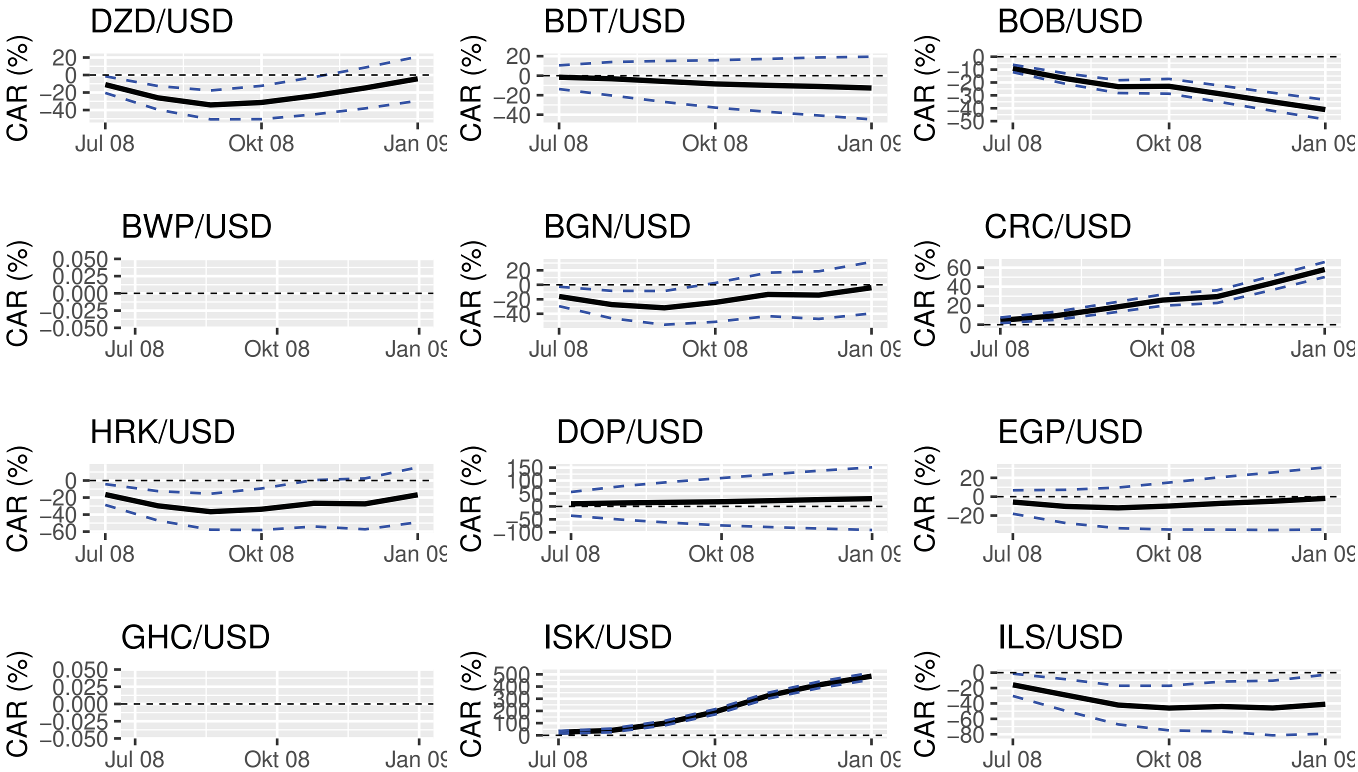


Figure A.8: **Cumulated abnormal returns for minor currencies part II for $h = 12$ during the global financial crisis period**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from July 2008 to January 2009 for minor currencies against the US dollar and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.

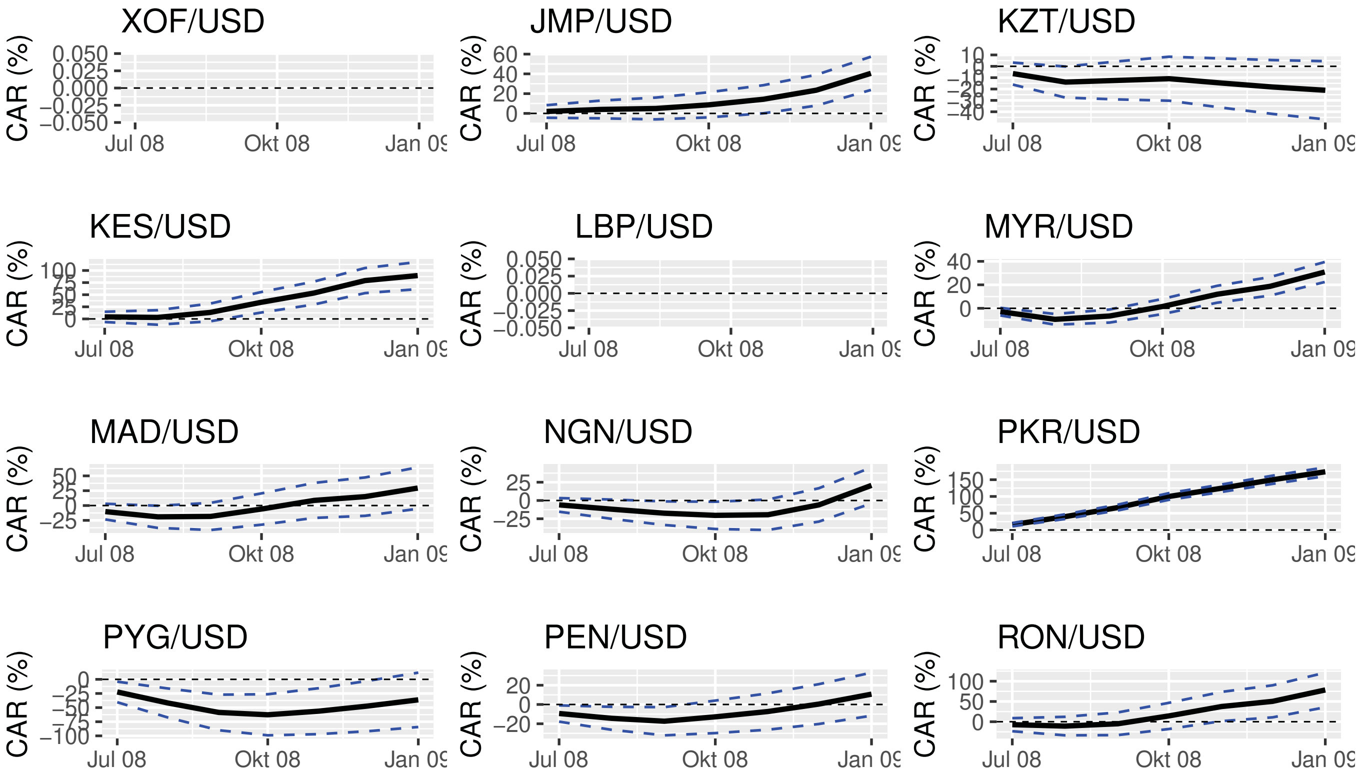


Figure A.9: **Cumulated abnormal returns for minor currencies part III for $h = 12$ during the global financial crisis period**

The plots shows the cumulated abnormal returns (CAR) in percentage terms computed recursively over the event window from July 2008 to January 2009 for minor currencies against the US dollar and a forecast horizon of $h = 12$. The solid black line visualizes the CAR in %, the dashed blue lines represent the 95% confidence interval and the dashed black line illustrates the null hypothesis of no abnormal returns. See Table A.1 for the currencies codes.