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Abstract

We propose measures of financial market stress for forty-six countries and regions across the world. Our measures indicate that worldwide financial market stresses rose significantly in March following the widespread economic shutdowns in the wake of the COVID-19 pandemic. However, hardly anywhere in the world did these March peaks in financial stresses reach those seen during the trough of the 2007-09 Global Financial Crisis. Since March, financial market conditions normalized rapidly with financial market stresses around average levels. We also show that our financial stress measures have predictive power for the near-term economic outlook across most parts of the world, with the exception of China. A structural Bayesian VAR analysis indicates that historically, financial stress shocks, irrespective of the source of the shock, have significant impact on global economic activity, but in particular that emerging market economies are usually hit more severely than advanced economies.

Key words: financial markets, financial stress indices, emerging markets, advanced economies, SVAR

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To view the authors' disclosure statements, visit
https://www.newyorkfed.org/research/staff_reports/sr940.html.

1 Introduction

This note provides a description of summary measures of financial market stresses for advanced and emerging economies, their usefulness for near-term forecasting, as well as quantifying the macroeconomic impact of financial stress shocks on the different economies.

The main takeaways from our work are as follows. Firstly, since the onset of the COVID-19 pandemic financial market stress levels have risen substantially, with the advanced economies being the ones with the higher stress levels. Nonetheless, these stress levels generally have not reached the levels seen at the trough of the 2008-09 Global Financial Crisis. This possibly reflects the fact that this time around the source of the shock is not placed within the financial sector. Since March, stress levels have eased significantly.

Furthermore, changing levels of financial market stress contain useful information for the near-term outlook of economic activity in both advanced and emerging market economies, with the exception of China. The deteriorating financial market conditions during February and March led to a significant ramping up of the downside risk to the outlook of economic activity across the world. As financial stresses eased some of this downside risk lessened, particularly so for emerging market economies.

We then use a Bayesian VAR model estimated for the period 2000-2019, to show that financial stress shocks, whether they are global or emerging market-specific, have significant effects on GDP in both advanced and emerging market economies. However, for both types of shocks the impact on emerging market economies is both larger in magnitude and more persistent. Both global and emerging market-specific stress shocks result in the weakening of emerging market economies' currencies relative to the U.S. dollar. Under the assumption that the observed deterioration in EM financial market conditions (equal to around 2 points in the EM FSI) was driven by an EM-specific financial stress shock, as identified in our BVAR model, the resulting decline in EM GDP and world imports would result in pushing US GDP about 0.5% below trend after a year.

The remainder of this note is organized as follows. We describe the construction of our financial stress indices in Section 2. Then, we link in Section 3, using several approaches, our stress indices to economic activity in the major economic regions across the world. Finally, we conclude in Section 4

2 Financial Stress Indices: Description

For 46 economies, both advanced and emerging market, we summarize developments in a range of financial market variables, equity indices and volatility, short- and long-term government bond yields, interbank spreads, corporate bond spreads, sovereign bond spreads

and convenience yield spreads, by means of principal component extraction. The resulting indices are such that a value of zero indicates average financial market stress, non-zero values measure the number of standard deviations the index deviates from zero where positive values signals increased financial market stress.

Generally, the set of financial market variables we look at for each country are drawn from the following list:

- Equity market cap index (usually at market capitalization if not available alternative index is used, such as MSCI).
- Equity cap index for the financial sector.
- Realized equity market volatility.
- 10-yr government bond yield.
- Short term government interest rate (1-yr government bond yield or 3-month T-bill yield, depending on availability).
- Yield curve spread: 10-yr government bond yield – short government interest rate.
- Interbank spread: local LIBOR rate (1 year or less depending on availability) – short term government interest rate.
- Corporate bond spreads:
 - For advanced economies and China we use a local currency domestic non-financial corporate bond yield – government bond yield, where
 - * Domestic local currency non-financial corporate bond effective yields equals a weighted average from effective yields on individual outstanding non-financial domestic firms’ bonds in local currency with a remaining maturity of 5 years at each point in time from the ICE bond data base. The weights reflect the relative share of the individual bonds.
 - * Domestic government bond effective yields equals a weighted average from effective yields on individual outstanding government bonds in local currency with a remaining maturity of 5 years at each point in time from the ICE bond data base.
 - For remaining economies we use instead JP-Morgan US dollar-based corporate bond spreads.

- JP-Morgan sovereign bond spreads in US dollars. Note: not included for the U.S. and in case of the euro area and its individual member states this is replaced by a GDP-weighted average of member states' (excl. Germany) government bond yield spreads relative to Germany or the individual member state's spread relative to Germany, respectively, both at 5-yr and 10-yr maturities.
- 5-yr government bond convenience yield spread relative to the U.S for the G10 economies (excl. the U.S.).
- 10-yr government bond convenience yield spread relative to the U.S for the G10 economies (excl. the U.S.).
 - The construction of these convenience yield spreads follows Du et al. (2018) and equal longer term covered interest rate parity deviations between the U.S. Treasury yield and the hedged yield on a corresponding government bond with local currency cash flows converted in fixed U.S. dollar cash flows corrected for mispricing in dollar swap markets. The more negative these spreads are the larger are safe haven inflows into dollar assets away from foreign assets.

This is the maximum pool of financial market variables. We collect variables for a total of 46 countries. However, for some (in particular emerging market) economies we have significantly less variables available. The underlying financial market variables are obtained from several commercial databases: Bloomberg, Haver DLX, ICE Bond Indices, and Thomson Reuters Datastream,

Before these variables are summarized in indices they need to be transformed to provide sensible dynamics. In case of the overall equity market and the financial sector equity variables we look at year-over-year growth rates, whereas for the remainder we consider levels. Then, we detrend the variables, except for the equity valuation variables, by means of a smoothly evolving trend¹ to cleanse the variables from persistently trending behavior.² Finally, the transformed variables are standardized, i.e., expressed in number of standard deviations away from a zero mean.

¹More specifically, we use as the trend the bi-weight kernel-based two-sided average as in Stock and Watson (2012). We use a 5-year window of data for the average at each point in time, which converges to a one-sided window at the start and end of the overall sample.

²A lot of this trending behavior is due to structural market developments unrelated to financial stress (or the absence of it). For example, corporate bond markets in the euro area have become increasingly more liquid since the late 1990s resulting in downward trends in euro area corporate bond spreads, which obviously does not mean that euro area financial conditions have become structurally looser over this period. In this respect we differ from the IMF and Bank of England, who produce similar measures, as they do not detrend their underlying data.

Economy wide financial stress is defined as common stress across the financial market variables for an economy. Simply averaging will not necessarily capture this so, in line with the literature, for each economy we extract the first principal component from the available standardized financial market variables, where the resulting weights for the variables reflect the degree to which they correlate with each other.

Financial stress indices are constructed for a total of 46 countries, as well as for some GDP-weighted aggregates: world, world excl. the U.S., Asia, Asia excl. China, emerging market countries, emerging market countries excl. China, the euro area, G10 economies excl. the U.S., Eastern Europe (EE) and Eastern Europe excl. Russia. Figures 1-4 below depict movements in our financial stress indices for the U.S., the G10 economies excl. the U.S. and the emerging market (EM) economies with and without China, whereas Appendix A reports all individual country FSIs and those for all regions.³ The parameters for the principal component weighting are done on a monthly basis, so the charts largely plots monthly data, but the monthly estimated weights can be combined with daily or weekly data to provide high frequency updates; this is done at the end of the sample in the figures. The samples plotted generally start around 1997-1998 for advanced economies and 2000-2001 the earliest for developing economies, and run up to August 28th 2020. Key takeaways from Figures 1-4 are that for most economies the degree of stress over the past six months seemed to have peaked in March, with the U.S. exhibiting the highest financial market stress levels, but this March peak suggested a significantly lower level of financial market stress than at the trough of the 2008-09 Global Financial Crisis.

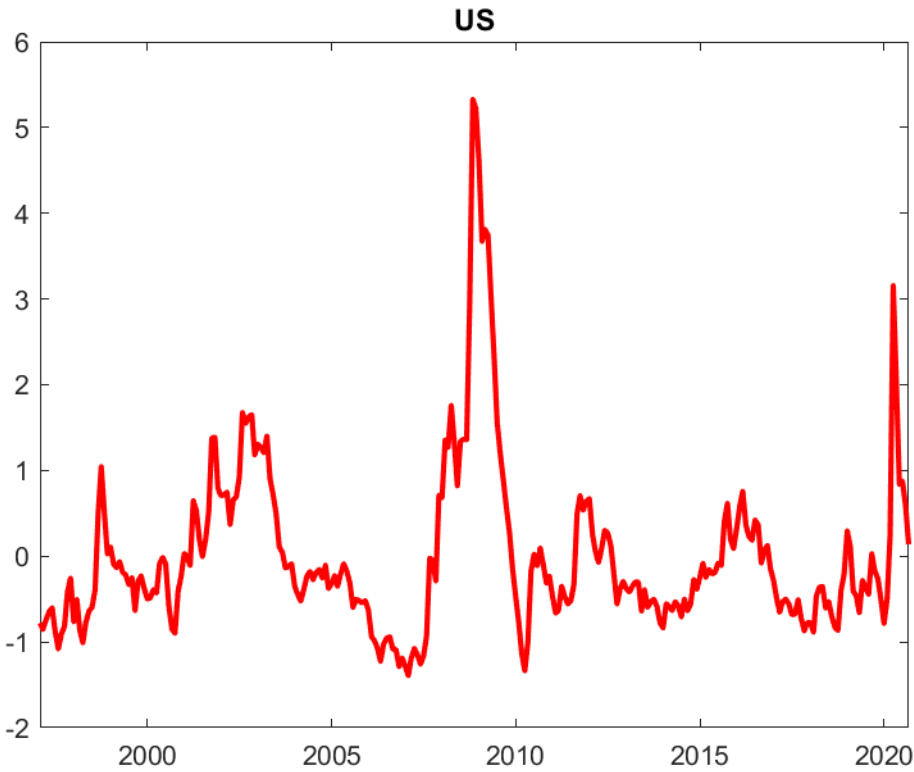
For the U.S. we compare in Figure 5 our FSI to other publicly available measures of U.S. financial stress from Bloomberg, the ECB (the composite index of systemic stress (CISS) for the U.S.), the Chicago FRB and the Kansas City FRB, which differ in terms of breadth and quantification. Figure 5 confirms that our recent readings on U.S. financial stress are in line with most alternative measures, except the Chicago FRB index, and historically correlates well with the majority of these measures.

In case of non-U.S. economies there not many alternative stress measures available. Figures 6 and 7 plot comparisons between our stress measure for the euro area and China, respectively, and measures from the Bloomberg, the ECB and Goldman Sachs in the former case and measures from Goldman Sachs and Citibank in the case of China.⁴ As

³G10 excl. U.S. encompasses Australia, Canada, Denmark, the euro area, Japan, New Zealand, Norway, Sweden, Switzerland, and the U.K. Emerging market economies here are defined as: Taiwan, Singapore, Israel, Thailand, China, Hong Kong, Philippines, Korea, Malaysia, Vietnam, Russia, Chile, India, South Africa, Indonesia, Brazil, Colombia, Mexico, Turkey, Argentina.

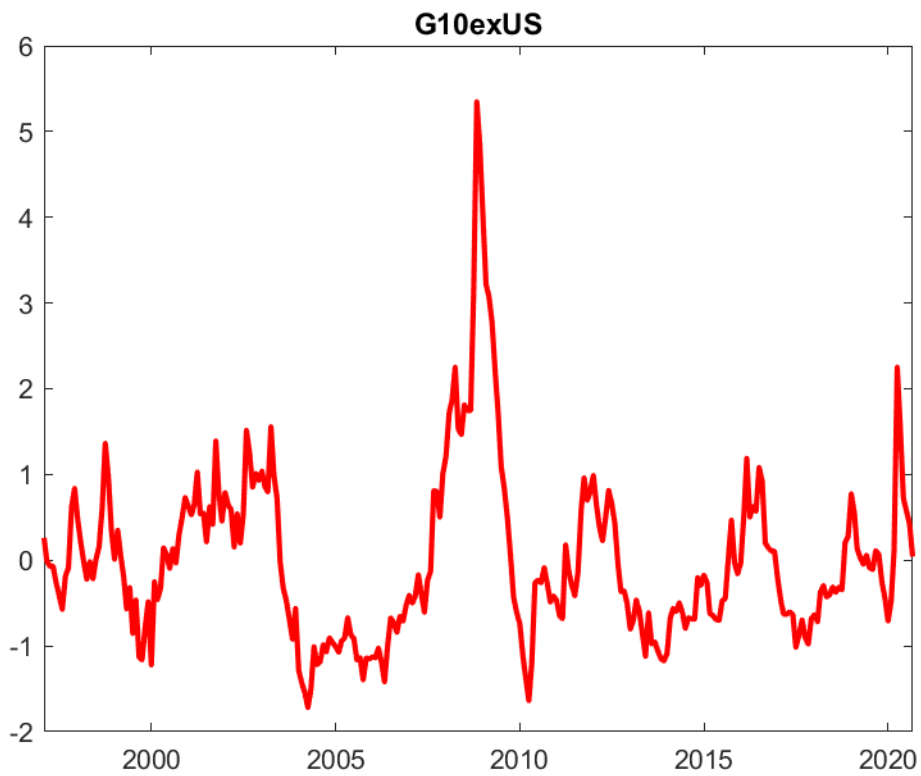
⁴These alternative financial stress measures were obtained from Bloomberg, except for the U.S. and euro area CISS measures which were taken directly from the ECB website. Note that all measures in Figures 5-7 are standardized to have a mean of 0 and a standard deviation of 1, and there are not depicted in their original units. This is done to make the comparison easier.

Figure 1: U.S. Financial stress index



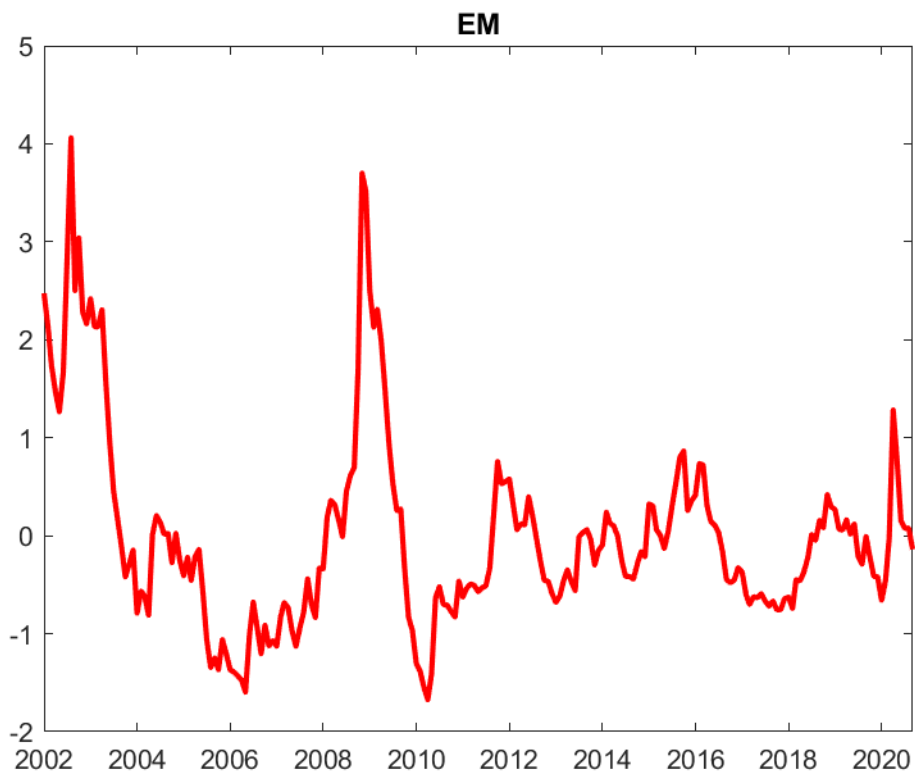
Notes: In the figure 0 indicates average stress levels, positive values measures the number of standard deviations stress levels are higher than average and *vice versa* for negative values.

Figure 2: G10 Economies' financial stress index



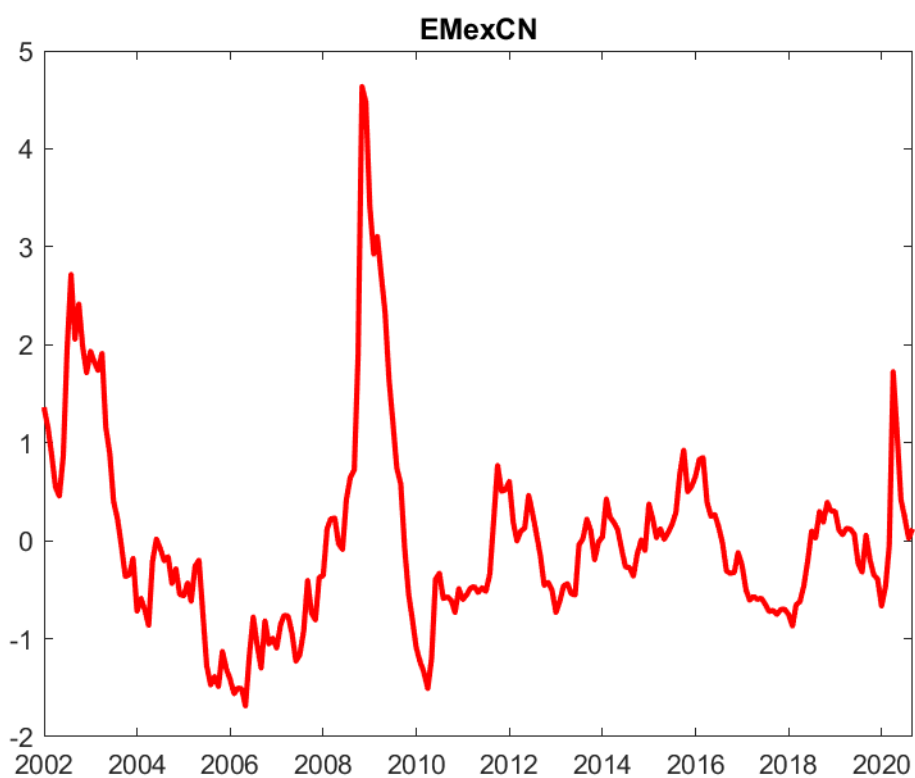
Notes: In the figure 0 indicates average stress levels, positive values measures the number of standard deviations stress levels are higher than average and *vice versa* for negative values.

Figure 3: Emerging market economies' financial stress index



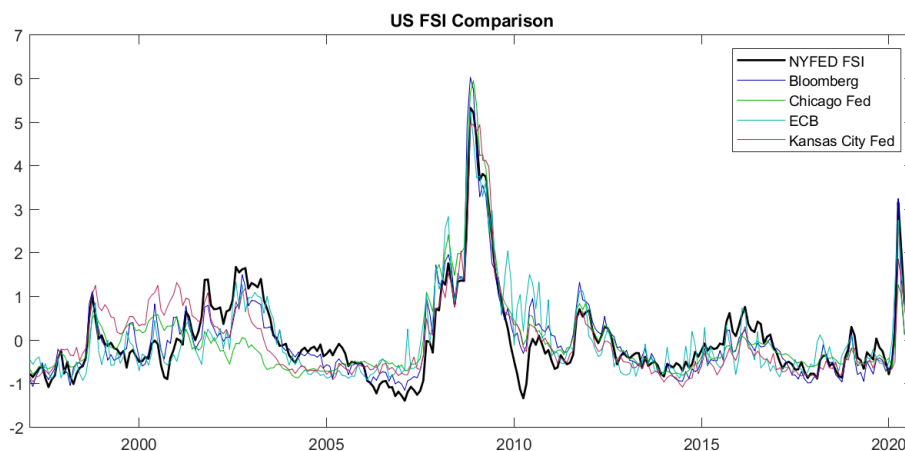
Notes: In the figure 0 indicates average stress levels, positive values measures the number of standard deviations stress levels are higher than average and *vice versa* for negative values.

Figure 4: Emerging market (excluding China) economies' financial stress index



Notes: In the figure 0 indicates average stress levels, positive values measures the number of standard deviations stress levels are higher than average and *vice versa* for negative values.

Figure 5: U.S. Financial stress index comparison



Notes: The figure plots the levels of different financial stress indices: ours (NYFED FSI), from Bloomberg, the NFCI from the Chicago Fed, the CISS index from the ECB and the Kansas City Fed financial stress index. The series are standardized over the sample and thus measures the deviation from the historical average in standard deviation terms.

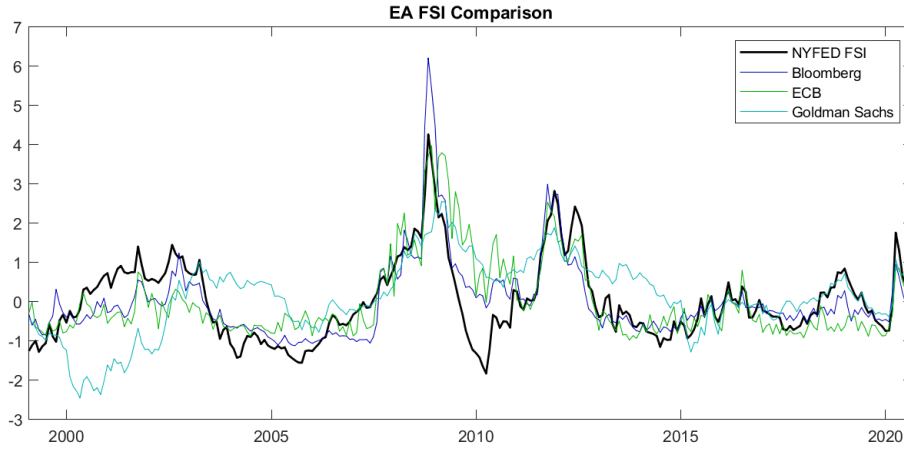
was the case for the U.S., readings on financial stresses in the euro area and China from our measure are broadly in line with most alternative measures.

How do the measures presented here differ from global financial stress indices constructed elsewhere? Our measures closely resemble those produced by the IMF,⁵ both in terms of the number of countries as well as the variables included. In terms of variables included, the IMF uses real short term interest rates whereas we use nominal short term interest rates, and adds real house prices and debt-weighted exchange rate indices (for EM economies only). We, instead, do not include house prices and exchange rate measures, but add financial sector market cap equity indices as well as convenience yield spreads relative to the US for the advanced economies. The absence of housing prices allows us to update the indices on a more frequent basis. Also, both exchange rates and house prices we view as variables that are impacted by a range of developments of which financial market stress is only one. Separating them out allows us to quantify the different effects on house prices and exchange rates.

The Bank of England, in addition, also produces financial condition indices for a similar set of countries as both the IMF and us, where they generally use the same set of variables as used here, minus the short-term interest rate, as well as the absence of convenience yield

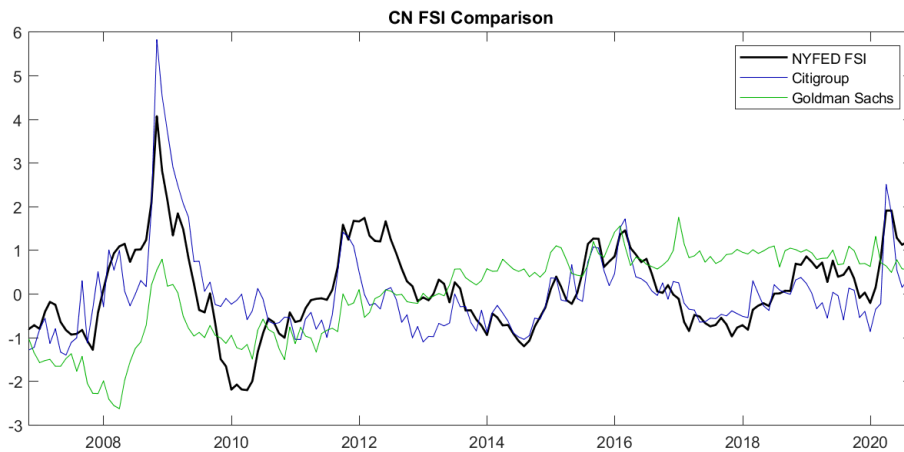
⁵IMF Global Financial Stability Report, October 2018, Online Annex 1.1 Technical Note (<https://www.imf.org/ /media/Files/Publications/GFSR/2018/Oct/CH1/doc/Annex1-1.ashx>).

Figure 6: Euro area Financial stress index comparison



Notes: The figure plots the levels of different financial stress indices: ours (NYFED FSI), from Bloomberg, the CISS index from the ECB and from Goldman Sachs. The series are standardized over the sample and thus measures the deviation from the historical average in standard deviation terms.

Figure 7: China Financial stress index comparison



Notes: The figure plots the levels of different financial stress indices: ours (NYFED FSI), from Bloomberg, from Citibank, and from Goldman Sachs. The series are standardized over the sample and thus measures the deviation from the historical average in standard deviation terms.

and local currency corporate bond spreads for advanced economies; see Eguren-Martin and Sokol (2019). Like done in this note, both the IMF and the Bank of England summarize the developments for each economies by means of principal component analysis.

3 Financial Stress Indices and Economic Performance

The financial stress indices purely measure the degree of financial market stress, not the extent to which worsening financial conditions have ex ante a contractionary impact on real activity. One way to gauge the impact of changing levels of financial stress on economic activity is to run predictive regressions in which k-months ahead growth in industrial production (IP) is regressed on current and lagged changes in the financial stress index (FSI) and lagged monthly growth rates of IP:

$$\Delta IP_{(t+k,t)} = \alpha + \sum_{i=0}^2 \beta_i \Delta FSI_{t-i} + \sum_{i=1}^p \gamma_i \Delta IP_{(t-i)} + \epsilon_{t+k,t}. \quad (1)$$

In (1) a lagged monthly growth rate of IP is used as in practice there is a one-month publication delay of IP date (e.g., in May one those not observe May IP data). In fact for a lot of economies, both advanced and emerging, the publication lag is sometimes longer and missing observations are imputed using corresponding manufacturing PMI data.⁶ For forecasting purposes model (1) is estimated recursively every month starting in January 2006 going back to 2000 using an expanding history of data and at each of these months a k-month ahead IP growth forecast is generated. The forecast errors of IP growth predictions based on (1) are then compared to those of a benchmark model without the financial stress index:

$$\Delta IP_{(t+k,t)} = \alpha + \sum_{i=1}^p \gamma_i \Delta IP_{(t-i)} + \epsilon_{t+k,t}, \quad (2)$$

with lag order p selected by BIC (which is generally around 2 or 3) and this lag order is also used in (1) so that (1) is nested in (2).

Table 1 presents ratios of the mean of squared forecast errors (MSFE) of model (1) versus model (2), where a ratio smaller than 1 suggest that the inclusion of financial stress indices improves the accuracy for future IP growth k-months ahead (the ratio essentially measure the relative forecast errors variances). The results in Table 1 do suggest that the indices contain useful information regarding risks to future economic activity in for a range of economies, with the possible exception of China. The usage of our financial stress indices provides improved predictive power, particularly at near-term horizons.

⁶The industrial production and PMI data we obtained from the Haver DLX database.

Table 1: Out-of-sample forecasting performance FSI model (1)

	$k = 1$	$k = 3$	$k = 6$	$k = 9$	$k = 12$
U.S.	0.85	0.80	0.86	0.92	0.95
G10 excl. U.S.	0.93	0.83	0.97	0.95	0.93
Emerging Markets	1.11	0.96	1.02	1.09	1.06
Emerging Markets excl. China	0.92	0.90	0.99	0.99	0.94

Notes: The table reports the ratio of the MSFE of (1) *vis-à-vis* model (2) at each horizon k (in months). The lags of IP growth in models (1) and (2) are set equal to the optimal lags that are picked from a range between 0 and 12 that minimize the BIC criterion for model (2). All models are estimated recursively with an expanding window with the first forecast generated in January 2006.

To quantify how risks to the outlook for manufacturing growth have evolved following financial market developments over the recent months, we employ the “growth-at-risk” framework of Adrian et al. (2019). In our context, and given the out-of-sample forecasting results in Table 1, this evolves using the right hand side variables of model (1) in conditional linear quantile regressions of one-year ahead growth of industrial production (IP) in the EM (excl. China), G10 (excl. U.S.) and U.S. economies, *i.e.*,

$$\Delta IP_{(t+12,t)}^\tau = \alpha + \sum_{i=0}^2 \beta_i^\tau \Delta FSI_{t-i} + \sum_{i=1}^p \gamma_i^\tau \Delta IP_{(t-i)} + \epsilon_{t+12,t}^\tau, \quad (3)$$

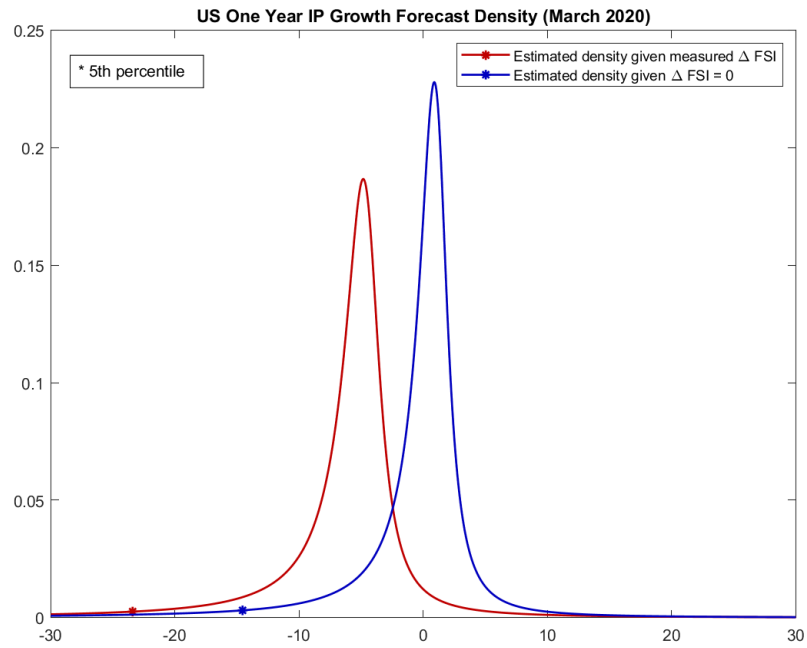
where $\Delta IP_{(t+12,t)}^\tau$ is the τ^{th} percentile of the one-year ahead IP growth.⁷ We estimate (3) for the $\tau = 5^{\text{th}}$, 25th, 75th, and 95th percentiles of 12-month ahead IP growth, which are then used to calibrate a skewed t-distribution that can be used to approximate the forecasted IP growth densities. These are reported in Figures 8-10, where each chart plots the densities at the end of March.

More specifically, figures 8-10 not only report on the implied one-year ahead IP growth densities given current real economic conditions and financial stress level changes, these figures also depict the implied densities when changes in financial market stress levels are set to zero. The difference between these densities highlights the impact of changing financial stress levels throughout the first quarter of 2020 on the predicted distribution of near-term future IP growth in March *ceteris paribus* real economic conditions. Figures 8-10 suggests that in March the predicted down side risk to manufacturing activity rose significantly for all economies with the large scale deterioration in financial market conditions that took place in March, especially outside of the U.S.

We next assess the joint movements for the FSIs across the different regions as well as

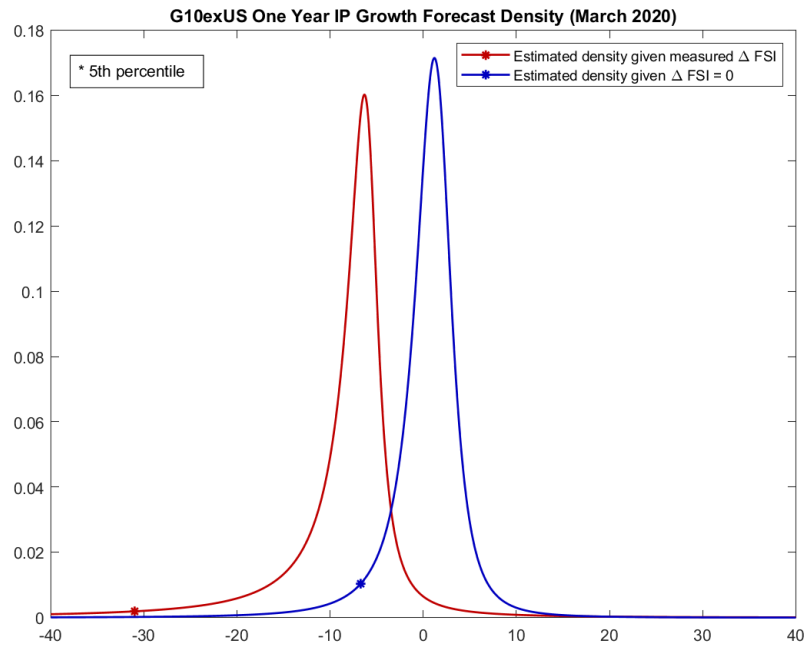
⁷For an overview on how to estimate conditional linear quantile regression, see, e.g., Koenker (2005).

Figure 8: U.S. one-year ahead IP growth forecast densities



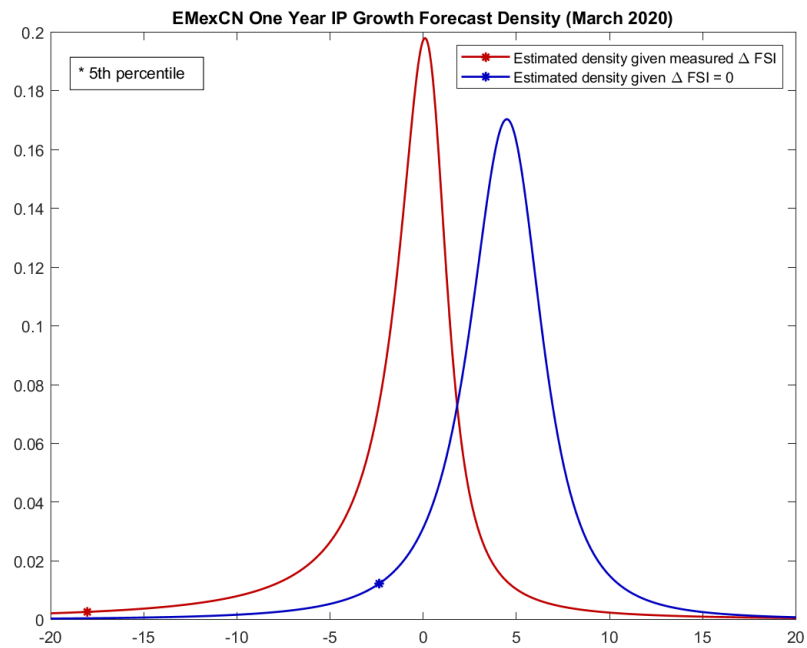
Notes: Industrial production (IP) growth forecast densities from a skewed t-distribution calibrated on estimates of 5th, 25th, 75th, 95th percentile conditional linear quantile regressions (3) at the end of March. The stars are the predicted one-year growth rates at the 5th percentile of the calibrated distribution (the x-axis represent 12-month growth rates of IP). The red density is one implied by the FSI and IP data at the end of March; the blue density is based on setting $\Delta FSI_t = \Delta FSI_{t-1} = \Delta FSI_{t-2} = 0$ with the specification as estimated and using IP data at the end of March.

Figure 9: G10 (excl. U.S.) one-year ahead IP growth forecast densities



Notes: Industrial production (IP) growth forecast densities from a skewed t-distribution calibrated on estimates of 5th, 25th, 75th, 95th percentile conditional linear quantile regressions (3) at the end of March. The stars are the predicted one-year growth rates at the 5th percentile of the calibrated distribution (the x-axis represent 12-month growth rates of IP). The red density is one implied by the FSI and IP data at the end of March; the blue density is based on setting $\Delta FSI_t = \Delta FSI_{t-1} = \Delta FSI_{t-2} = 0$ with the specification as estimated and using IP data at the end of March.

Figure 10: Emerging Market (excl. China) one-year ahead IP growth forecast densities



Notes: Industrial production (IP) growth forecast densities from a skewed t-distribution calibrated on estimates of 5th, 25th, 75th, 95th percentile conditional linear quantile regressions (3) at the end of March. The stars are the predicted one-year growth rates at the 5th percentile of the calibrated distribution (the x-axis represent 12-month growth rates of IP). The red density is one implied by the FSI and IP data at the end of March; the blue density is based on setting $\Delta FSI_t = \Delta FSI_{t-1} = \Delta FSI_{t-2} = 0$ with the specification as estimated and using IP data at the end of March.

how shocks to these FSIs transmit across the different economies. To do that we estimate a Bayesian vector autoregressive (BVAR) model consisting of k monthly variables:

$$\underbrace{Y_t}_{k \times 1} = \underbrace{D_0}_{k \times 1} + \sum_{i=1}^p \underbrace{D_i}_{k \times 1} \underbrace{Y_{t-i}}_{k \times 1} + \underbrace{\varepsilon_t}_{k \times 1}; \quad \varepsilon_t \sim iid(\mathbf{0}, \Omega^\varepsilon), \quad (4)$$

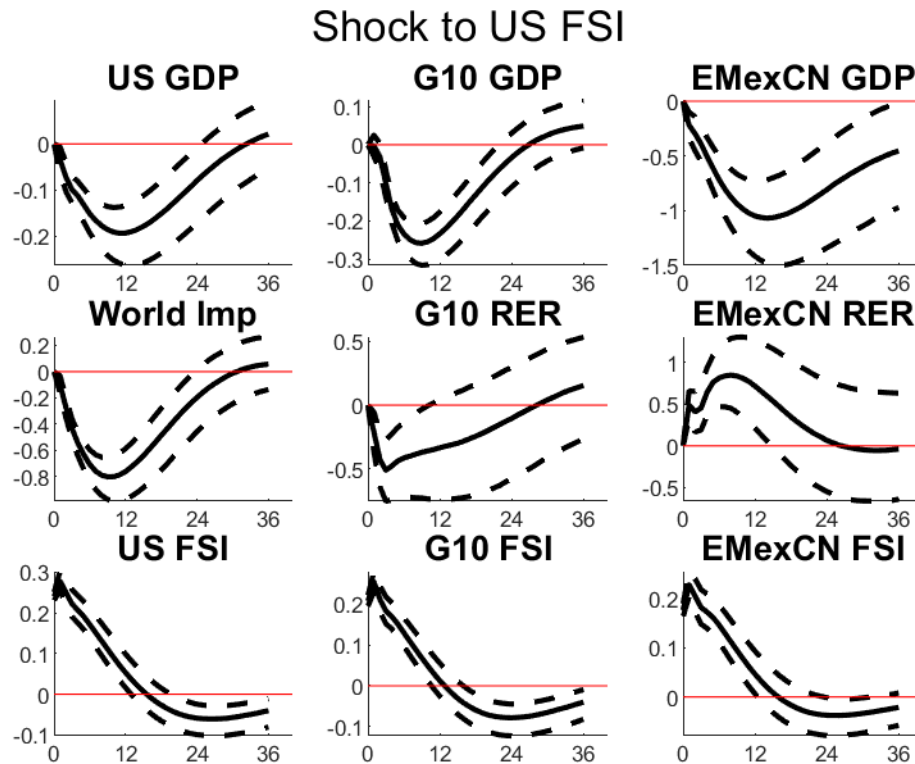
with $p = 3$ and the vector Y_t contains monthly data over the 2000-2019 sample with real GDP in the EM (excl. China), G10 (excl. U.S.) and U.S. economies (EMexCN GDP, G10 GDP, US GDP), real world imports (WorldImports), real exchange rates vs. the U.S. for the EM (excl. China) and G10 (excl. U.S.) economies and the respective FSIs. Monthly GDP series are constructed by interpolating quarterly real GDP series to the monthly frequency using monthly data on industrial production, retail sales, exports and imports within the Chow-Lin interpolation procedure, which is implemented as in Fernandez (1981), with the data being obtained from the Haver DLX database. The exception is the U.S. for which we use the monthly GDP series constructed by Macroeconomic Advisors (also retrieved from the Haver DLX database). Real world imports is from the CPB Netherlands' *World Trade Monitor*. Therefore, $Y_t = [\ln(\text{EMexCN GDP}) \ln(\text{G10 GDP}) \ln(\text{US GDP}) \ln(\text{World Imports}) \ln(\text{G10 RER}) \ln(\text{EMexCN RER}) \text{US FSI} \text{G10 FSI} \text{EMexCN FSI}]'$ and D_0 is a vector of deterministic terms with linear trends for the real GDP and world import variables and intercepts for the remaining series. BVAR model (4) is estimated with a Bayesian Monte Carlo Markov Chain (MCMC) simulation estimator based on a Minnesota prior on the $D_1 \cdots D_p$ parameter matrices, where following a burn-in period of 1000 draws the procedure uses 10000 MCMC draws to estimate the distribution of the VAR parameters.⁸

Shocks to US FSI and EM (excl. China) FSIs are identified by recursive identification where EM (excl. China) and G10 FSIs are allowed to react instantaneously to a US FSI shock, but the U.S. and G10 FSIs will not immediately react to an EM-specific FSI shock. This identification essentially treats a US FSI shock as the global financial market shock.

Figure 11 depicts the responses to a one standard deviation shock to the US FSI. Such a US stress shock results in increased financial stress across all regions, with GDP in the advanced economies falling around 0.25% below and EM (excl. China) GDP dropping over 1% below baseline after a year. EM currencies depreciate about 0.5% in real terms against the dollar over a similar horizon. Advanced economies seem to be back around trend after two years, whereas the adverse impact on EM (excl. China) GDP lingers on in the third year after the shock.

⁸The Minnesota prior uses the equivalent of 1 standard deviation to shrink the parameters of a variable in the VAR and 2 standard deviations to shrink distant lags of variables.

Figure 11: Impact of U.S. financial stress index shock

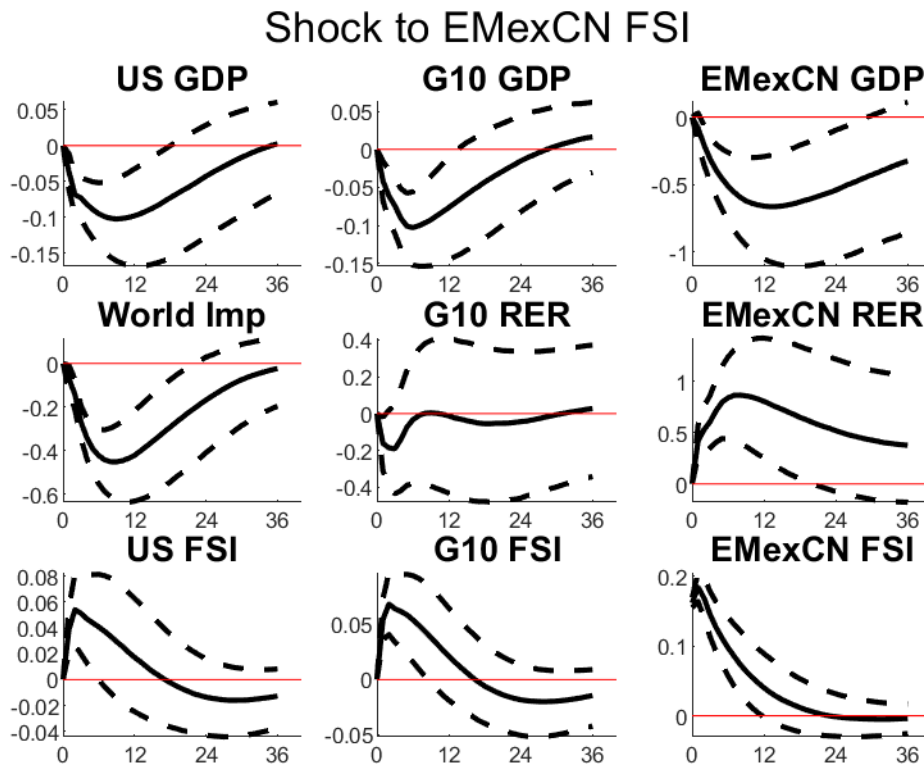


Notes: The graphs depict the response to a 1 standard deviation shock to the U.S. FSI in BVAR model (4) up to three year (36 months) after the shock. The BVAR model has a lag order $p = 3$ and the solid lines are the corresponding posterior medians with the dashed lines representing 68% confidence intervals based on 10000 MCMC draws. With the exception of the FSIs, the y-axis show the percentage deviation from baseline.

The responses for an EM-specific financial stress shock are reported in Figure 12. In this particular case, a year after a one standard deviation shock to the EM FSI, advanced economies' GDP moves about 0.1% below trend, EM GDP falls about 0.6% below trend and EM currencies depreciates around 1% relative to the dollar, and this persists beyond the 12-month horizon for EM (excl. China) economies in contrast to the advanced economies.. World imports fall about 0.6% below baseline after a year. Compared to the U.S. stress shock case, GDP in the respective economies are certainly adversely impacted, but at smaller magnitudes.

Comparing the EM response with those in advanced economies across both types of financial stress shocks, it becomes clear that real GDP in EM economies reacts with a larger magnitude than in advanced economies with the adverse impact being more persistent and

Figure 12: Impact of Emerging Market financial stress index shock



Notes: The graphs depict the response to a 1 standard deviation shock to the EM FSI in BVAR model (4) up to three year (36 months) after the shock. The BVAR model has a lag order $p = 3$ and the solid lines are the corresponding posterior medians with the dashed lines representing 68% confidence intervals based on 10000 MCMC draws. With the exception of the FSIs, the y-axis show the percentage deviation from baseline.

those types of shocks result in a significant real appreciation of the dollar relative to the EM currencies. The recent deterioration of EM (excl. China) financial market conditions appears to have been at its trough in March, as can be seen in Figure 4. A simple regression of the EM (excl. China) FSI on its own lags suggests that the residual of this regression for the EM (excl. China) FSI in March was about 4.75 times larger than the historical standard deviation of residuals in the autoregressive model of the EM (excl. China) FSI. Assuming this increased EM financial market stress was EM specific, our BVAR analysis then suggests that this could push US GDP about 0.5% below trend over a one year horizon, as GDP in EM and G10 economies as well as world imports slow down significantly.

4 Conclusions

In this note we introduce measures of financial market stress for a large number of countries and regions across the world. Our measures indicate that worldwide financial market stresses ramped up in March following the widespread economic shutdowns in the wake of the COVID-19 pandemic. Although stresses went up significantly in March, hardly anywhere in the world these March peaks in financial stresses reached those seen during the trough of the 2007-2009 Global Financial Crisis. Since March, financial market conditions normalized rapidly with financial market stresses around average levels.

We also show that across most parts of the world our financial stress measures have predictive power for the near-term economic outlook, with the exception of China. Based on this finding we utilize quantile regression to calibrate forecast densities for near-term manufacturing activity and a Bayesian VAR model to trace the impact of financial stress shocks on global economic activity. Our findings suggest that the March stress peak did significantly raised the downside risks to global manufacturing activity over the remainder of the year, especially outside of the U.S. The structural BVAR analysis indicated that historically financial stress shocks, irrespective of the source of the shock, have significant impact on global economic activity, but in particular Emerging Market economies are usually hit more severely than advanced economies.

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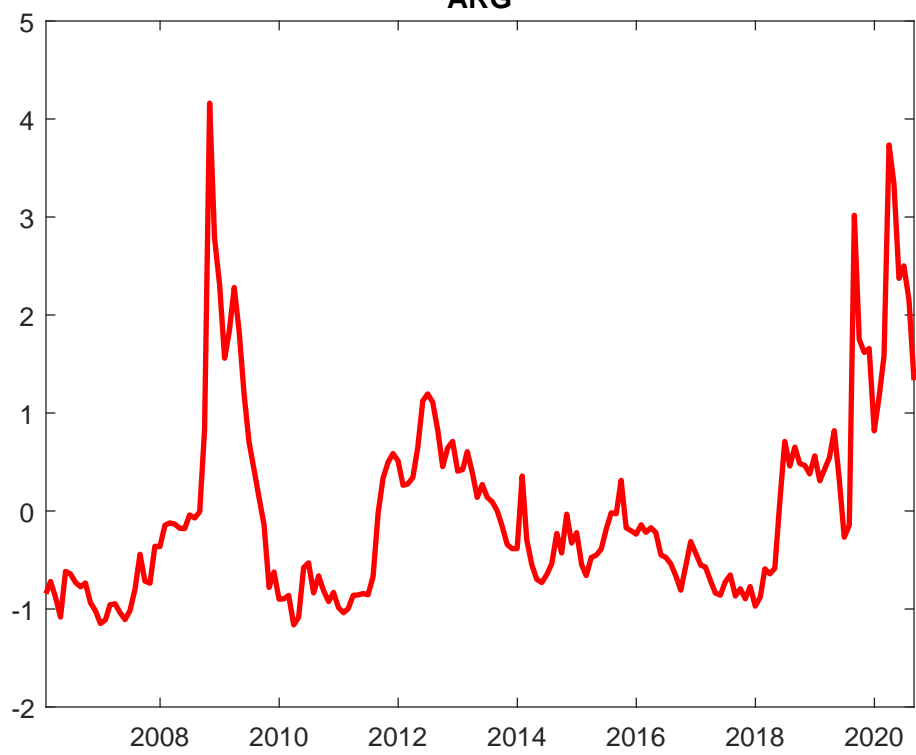
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A Financial Stress Indices: Full Set of Countries and Regions

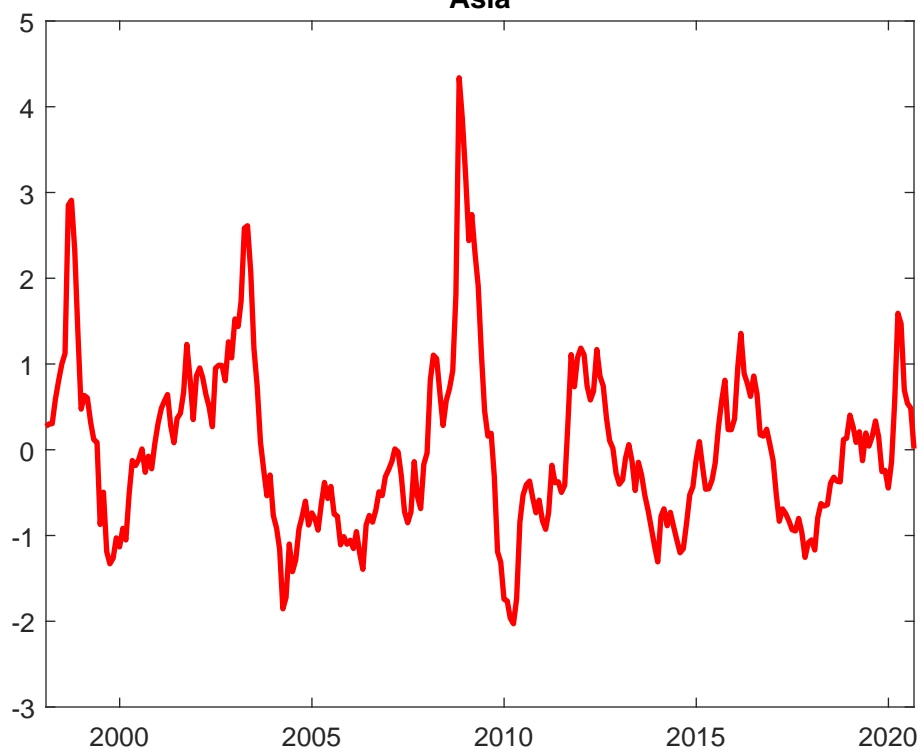
The charts in this Appendix report our constructed financial stress indices for (in this order): Argentina, the Asia region, the Asia (excl. China) region, Australia, Austria, Belgium, Bulgaria, Brazil, Canada, Switzerland (CHE), Chile, China, Columbia, Czech Republic, Germany (DEU), Denmark, the euro area, the Emerging Markets countries, the Emerging Markets (excl. China) countries, Spain (ESP), Finland, France, the G10 (excl. U.S.) countries, Greece, Hong Kong, Hungary, Indonesia (IDN), India, Ireland, Israel, Italy, Japan, South Korea (KOR), Mexico, Malaysia (MYS), Netherlands, Norway, New Zealand, Peru, Philippines, Poland, Portugal (PRT), Russia, Singapore, Sweden, Thailand, Total (all countries combined), Total excl. U.S., Turkey, Taiwan, U.K., U.S., Vietnam, South Africa (ZAF). The regions comprise of GDP-weighted averages of individual countries' FSI measures.

Note that in the figures a 0 indicates average stress levels, positive values measures the number of standard deviations stress levels are higher than average and *vice versa* for negative values.

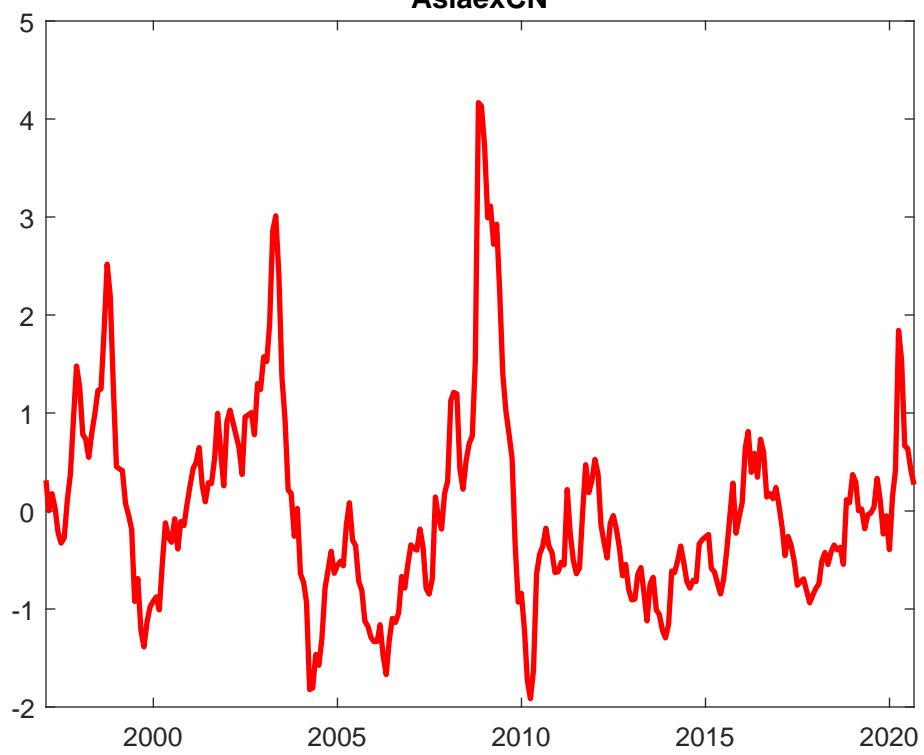
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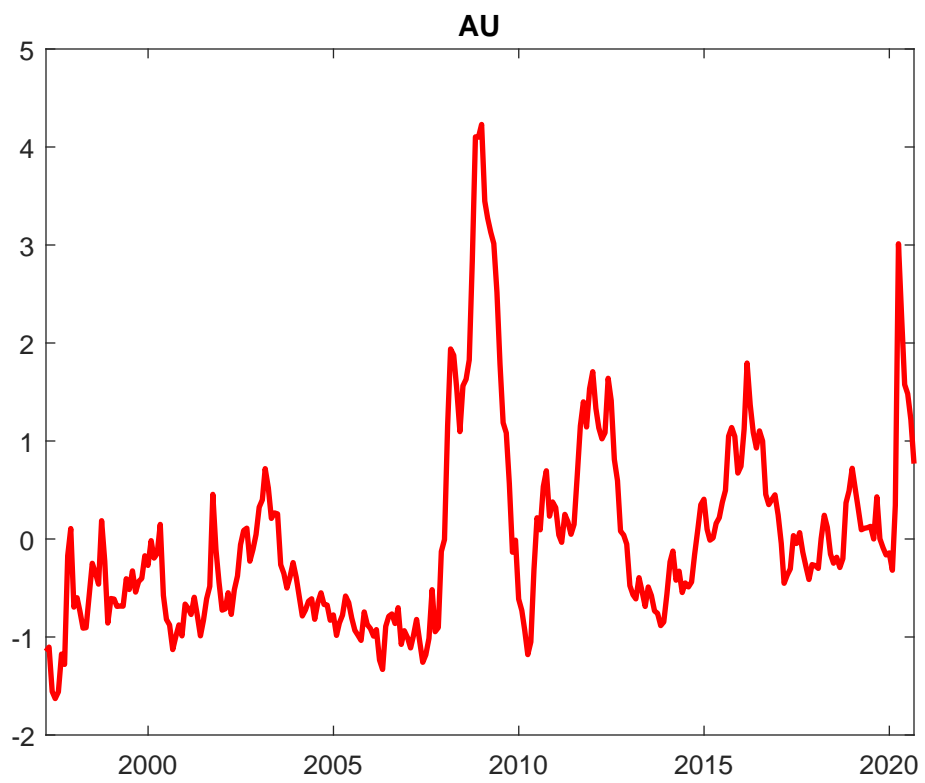


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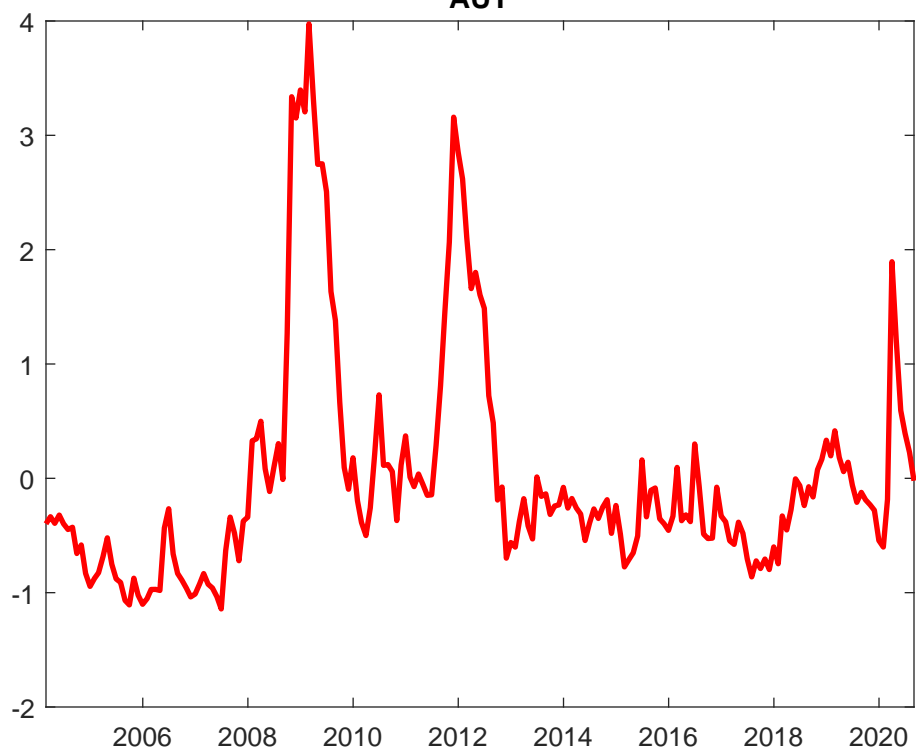


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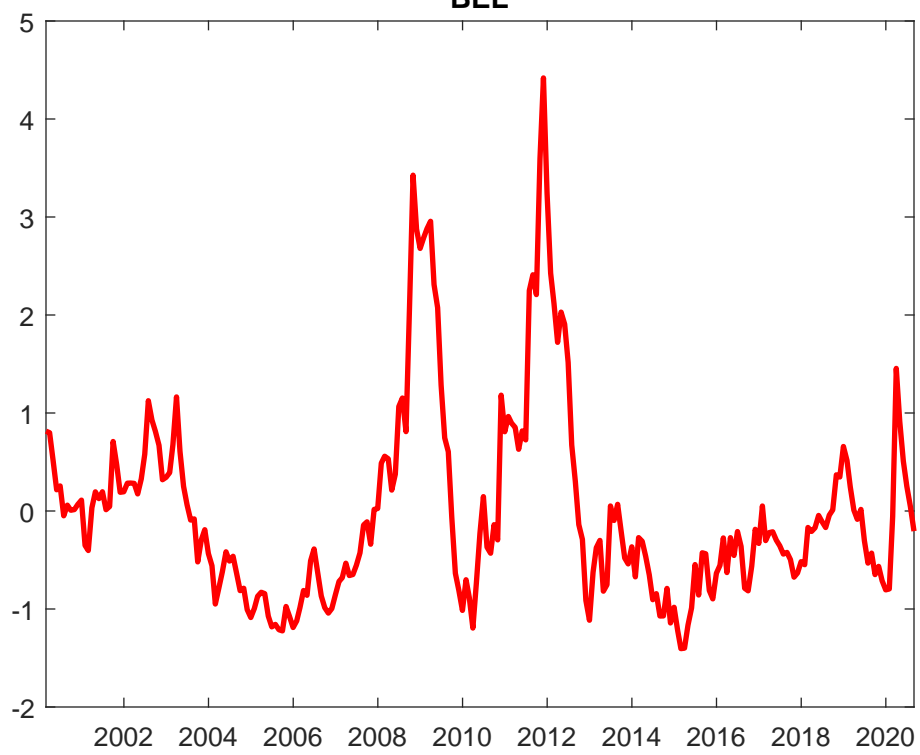




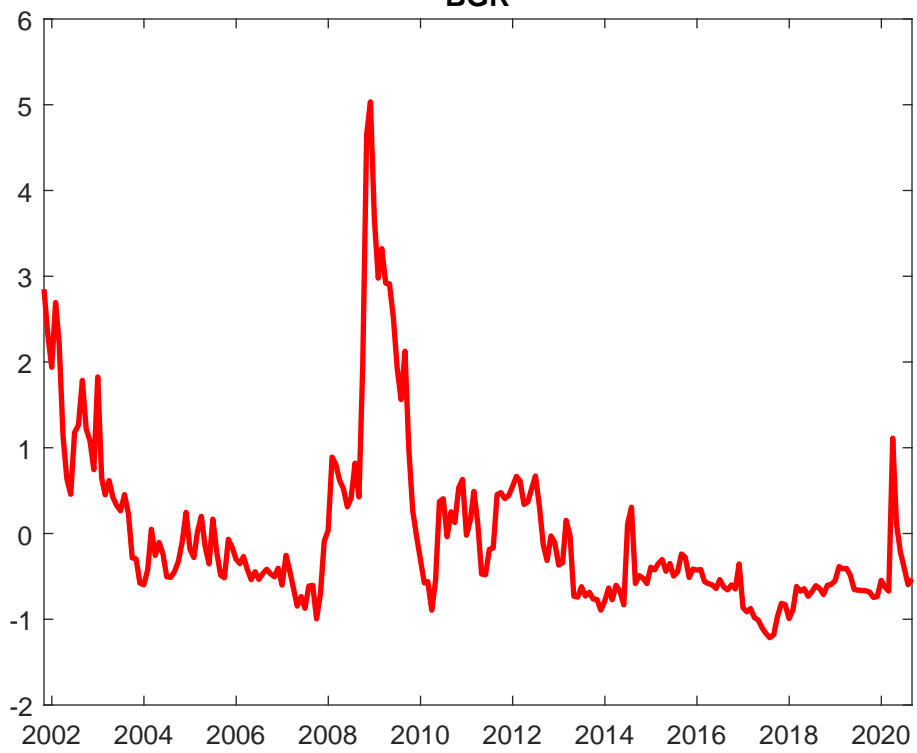
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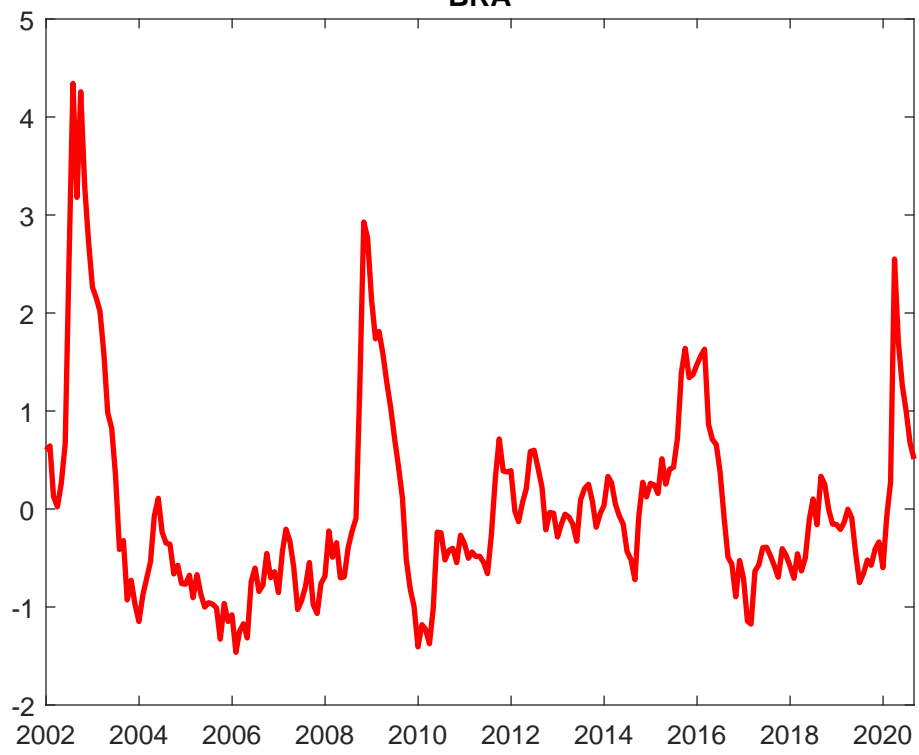
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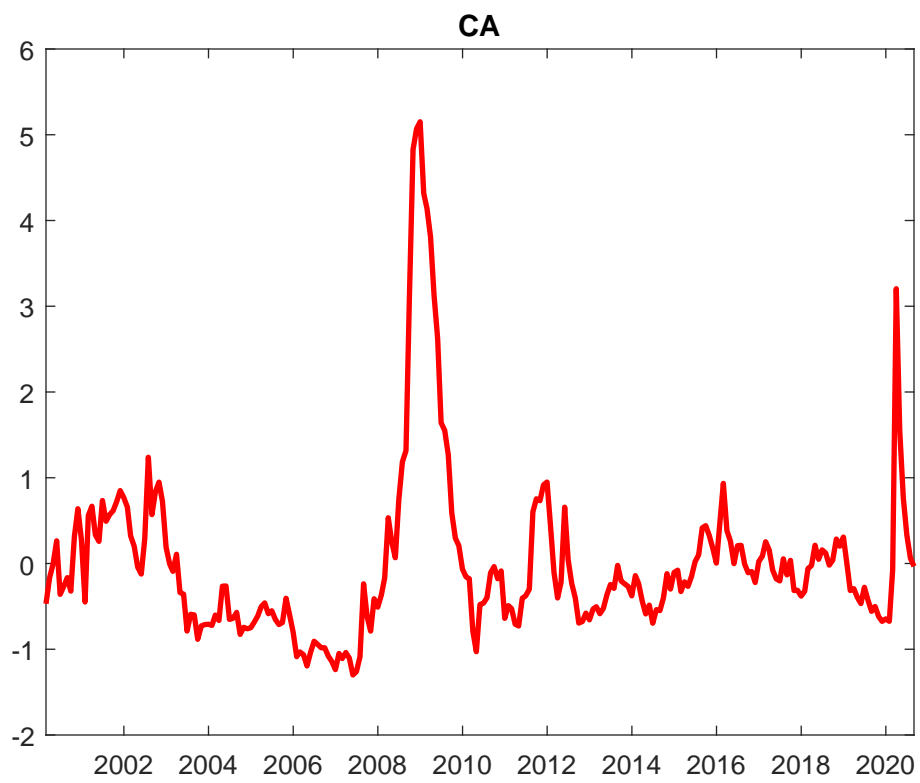


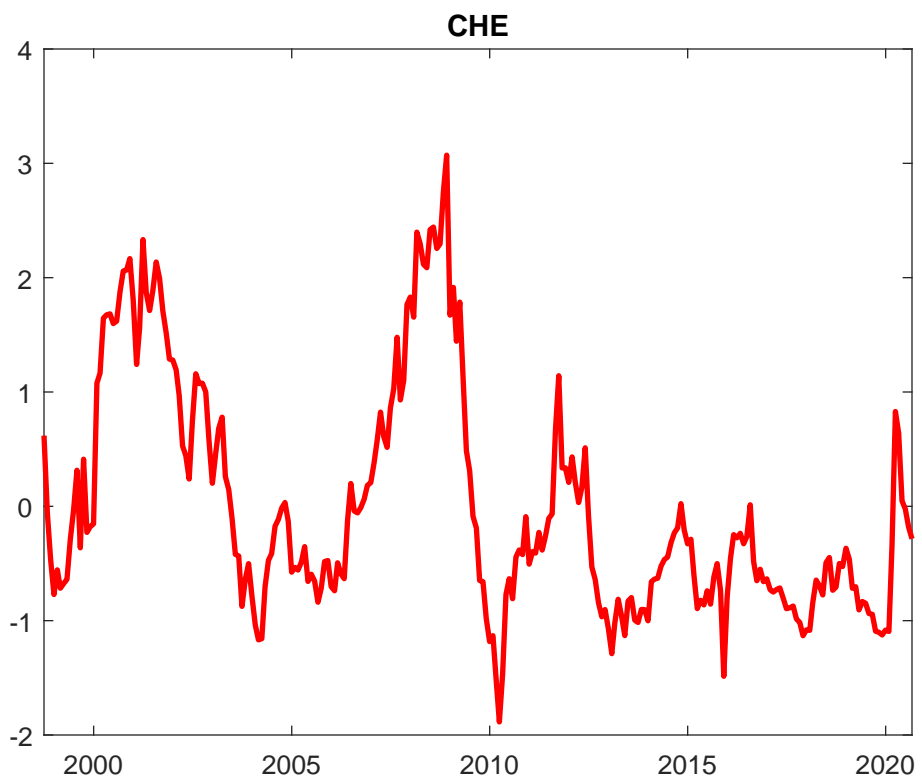
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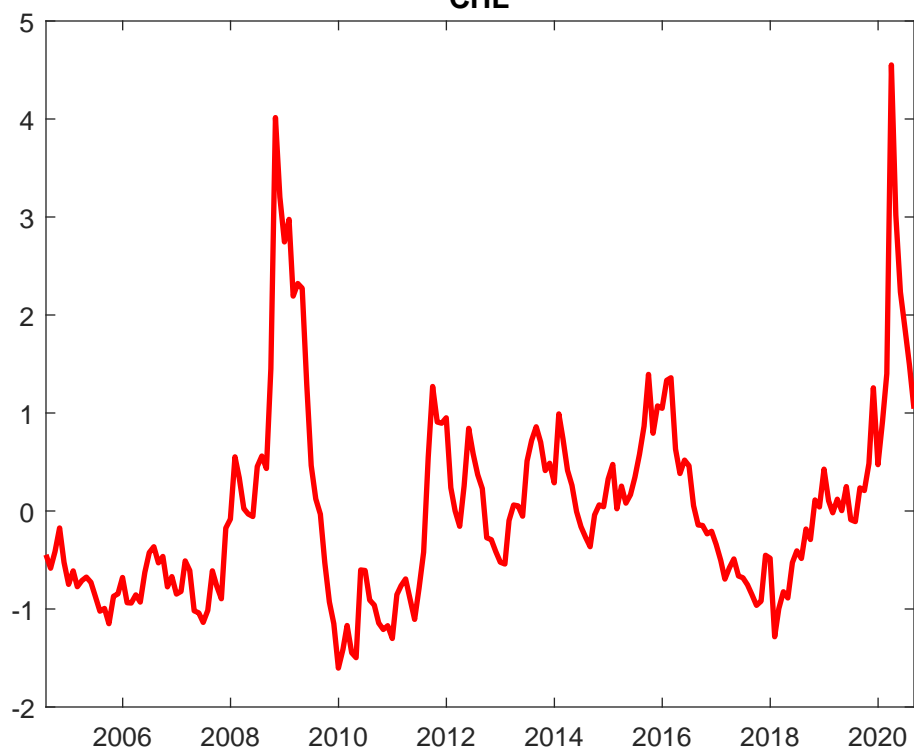
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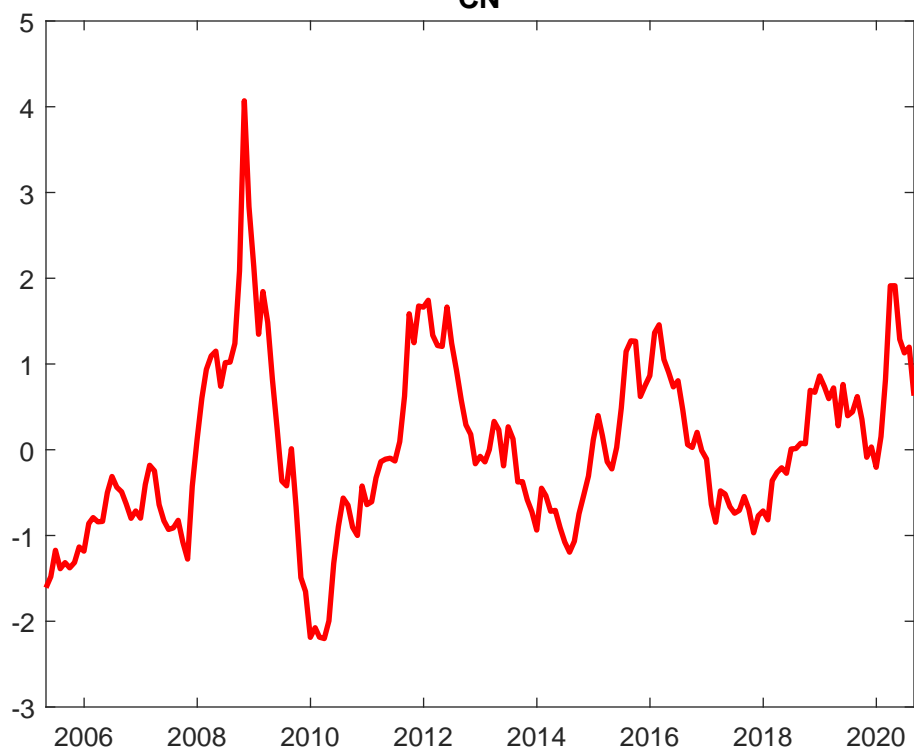




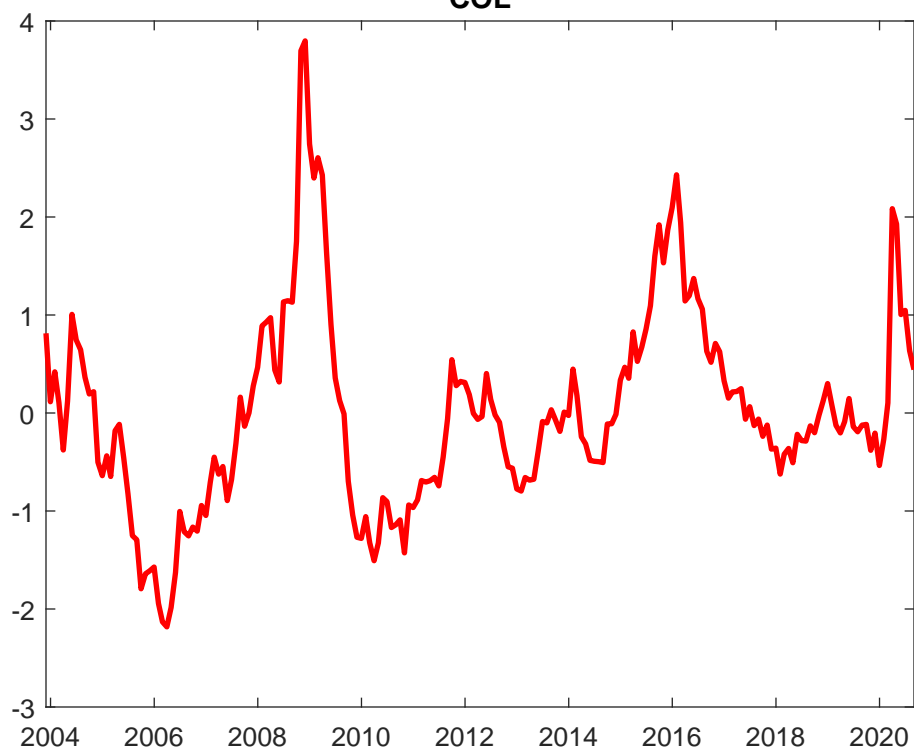
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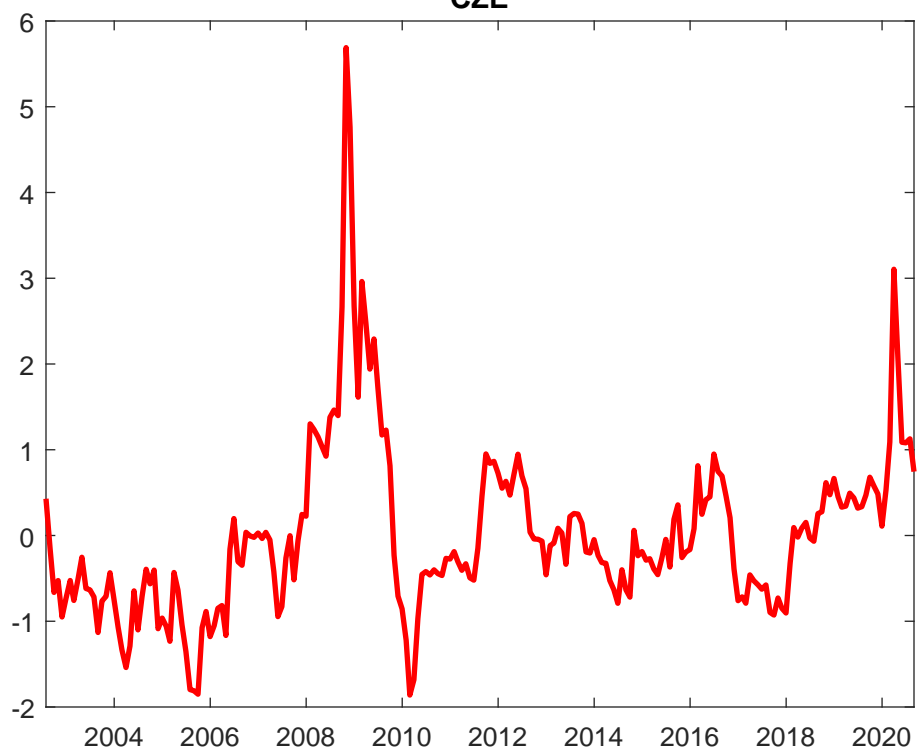
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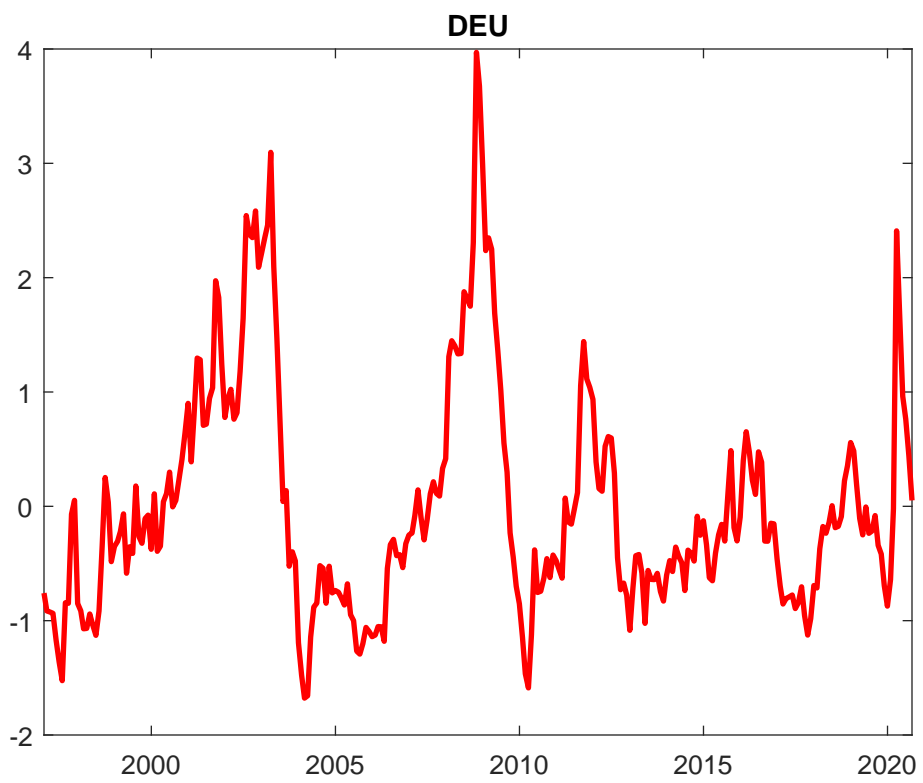


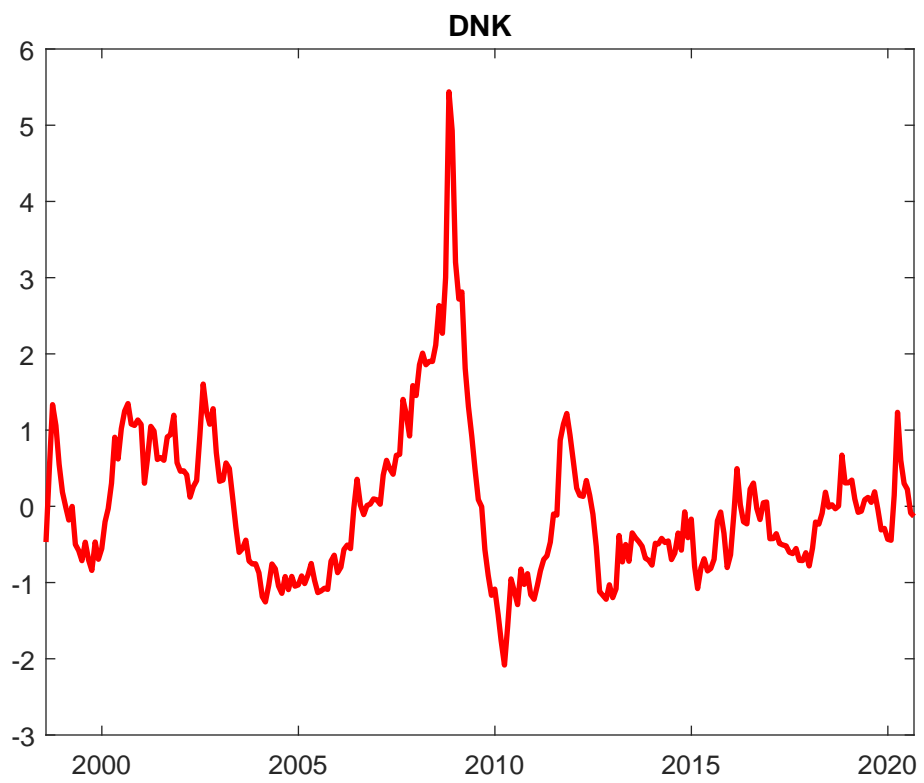
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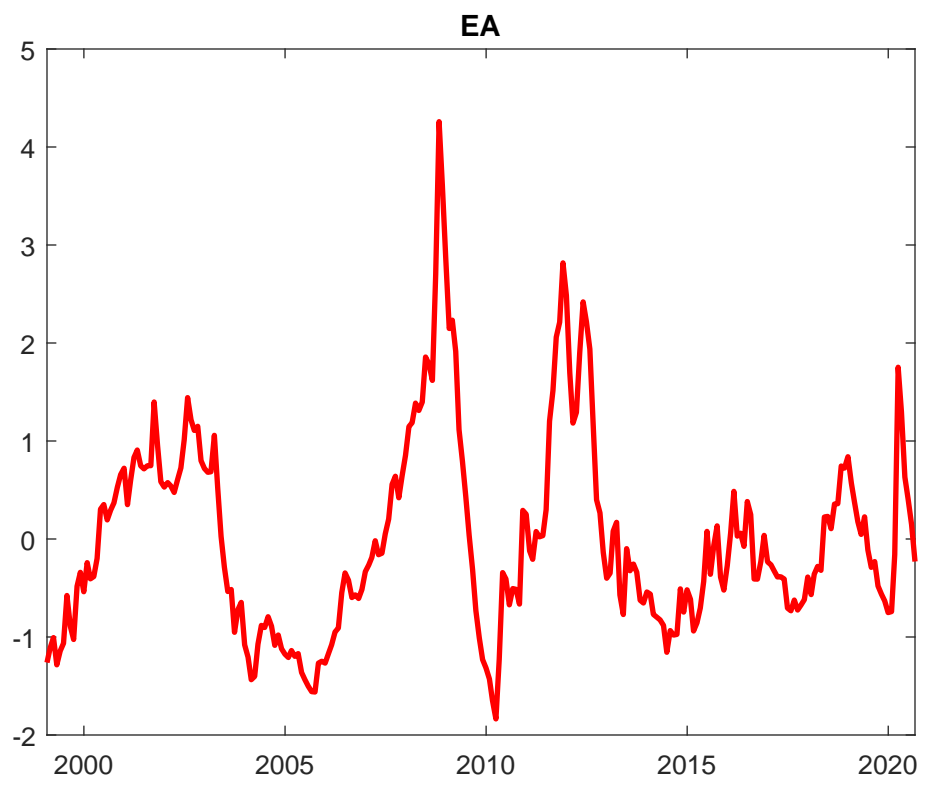


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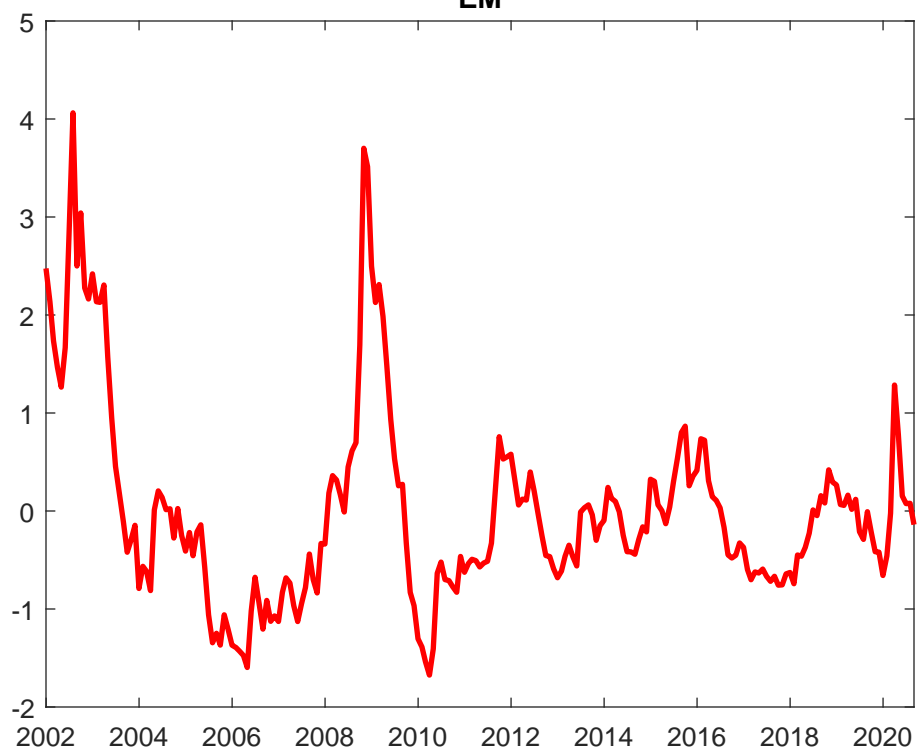




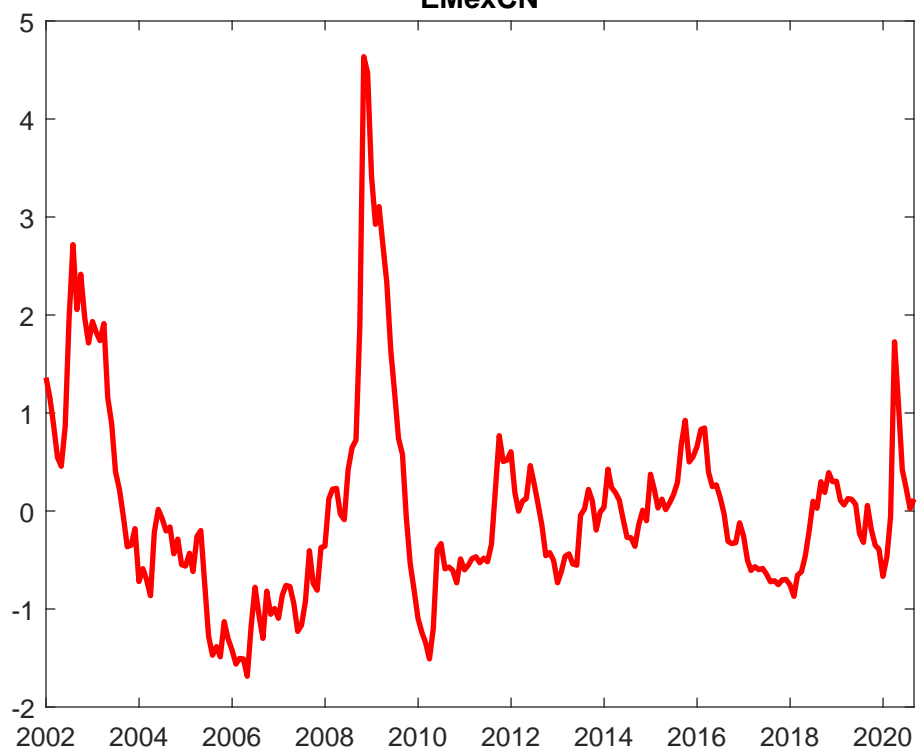




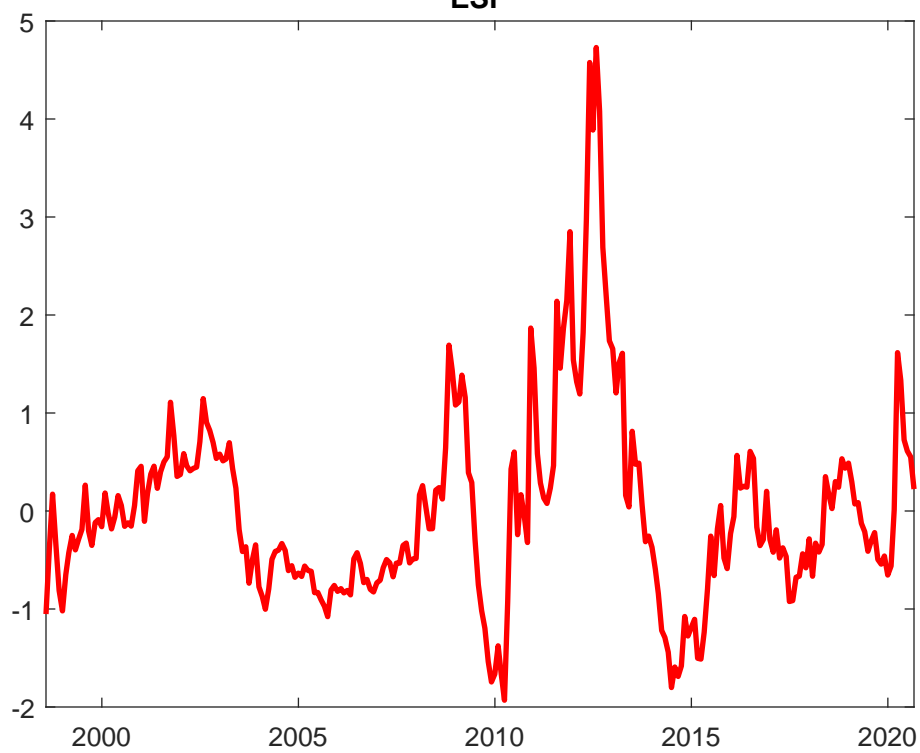
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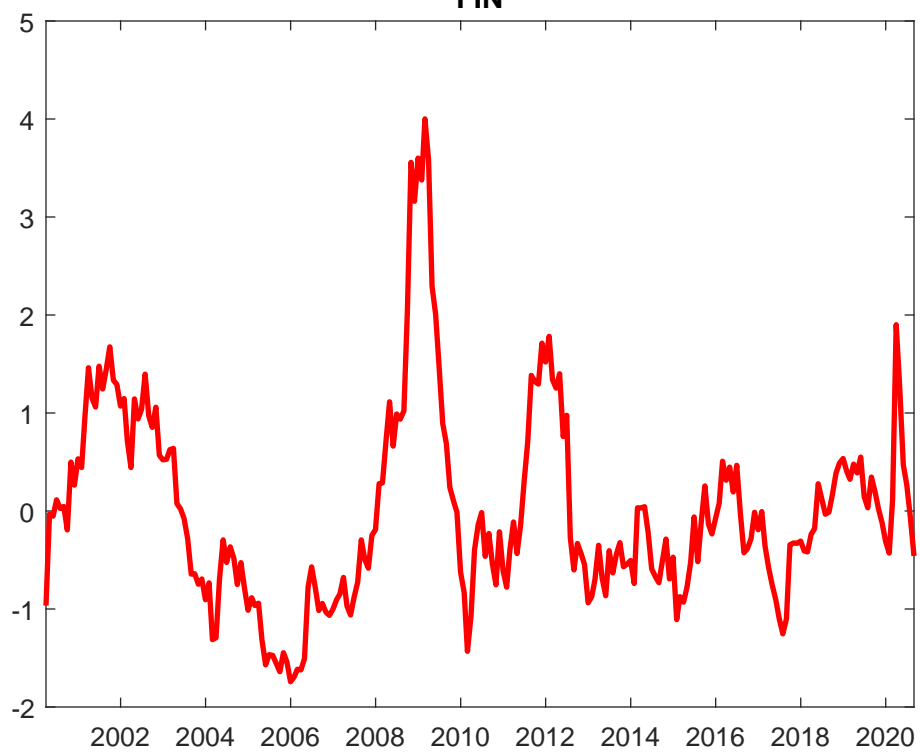
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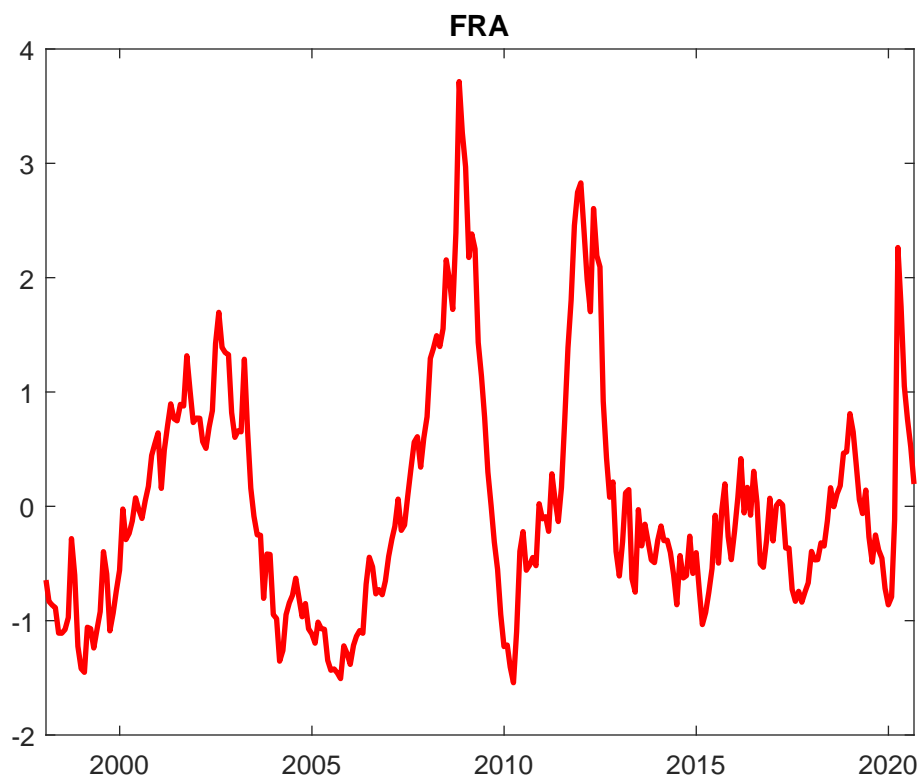


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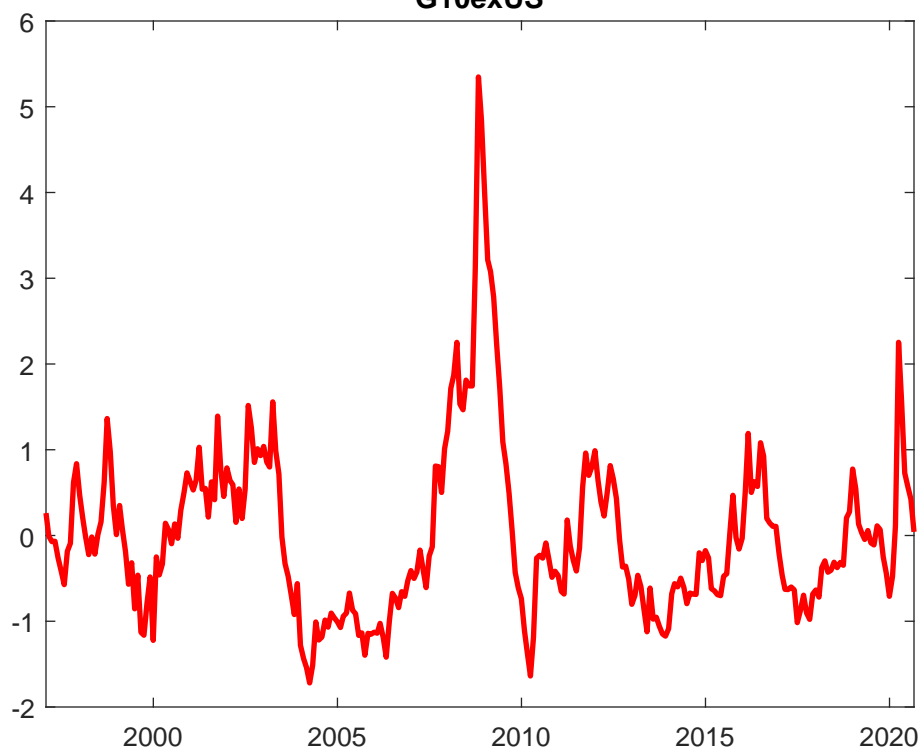


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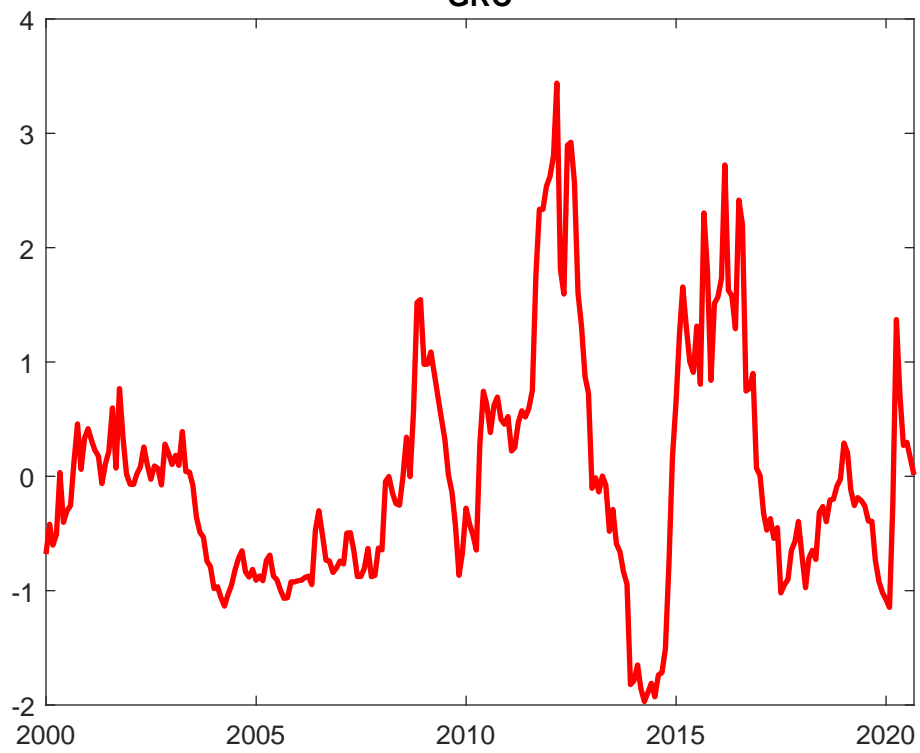




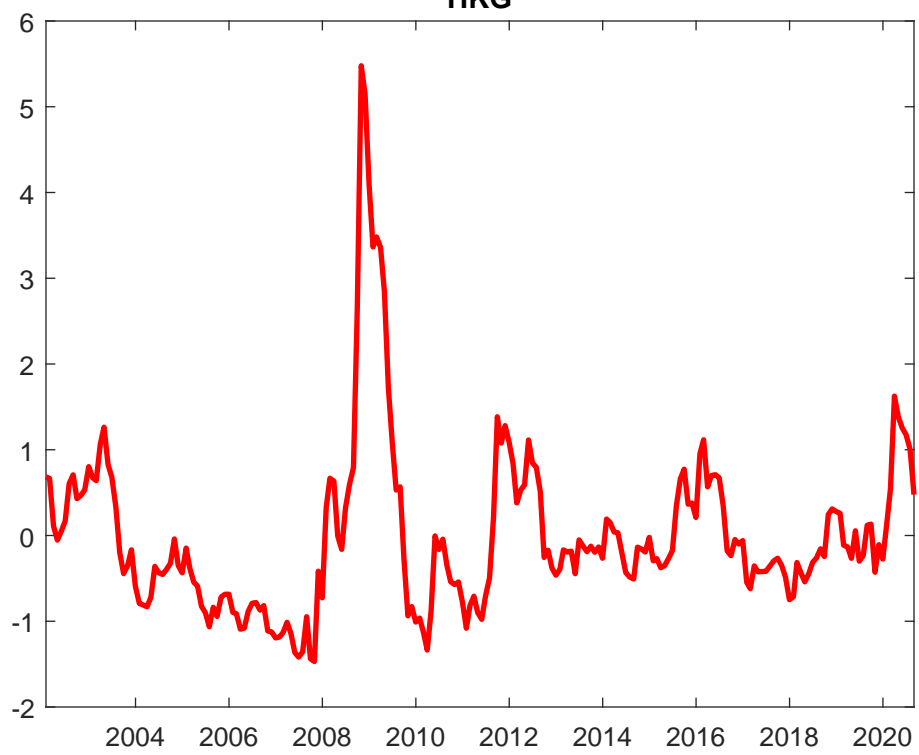
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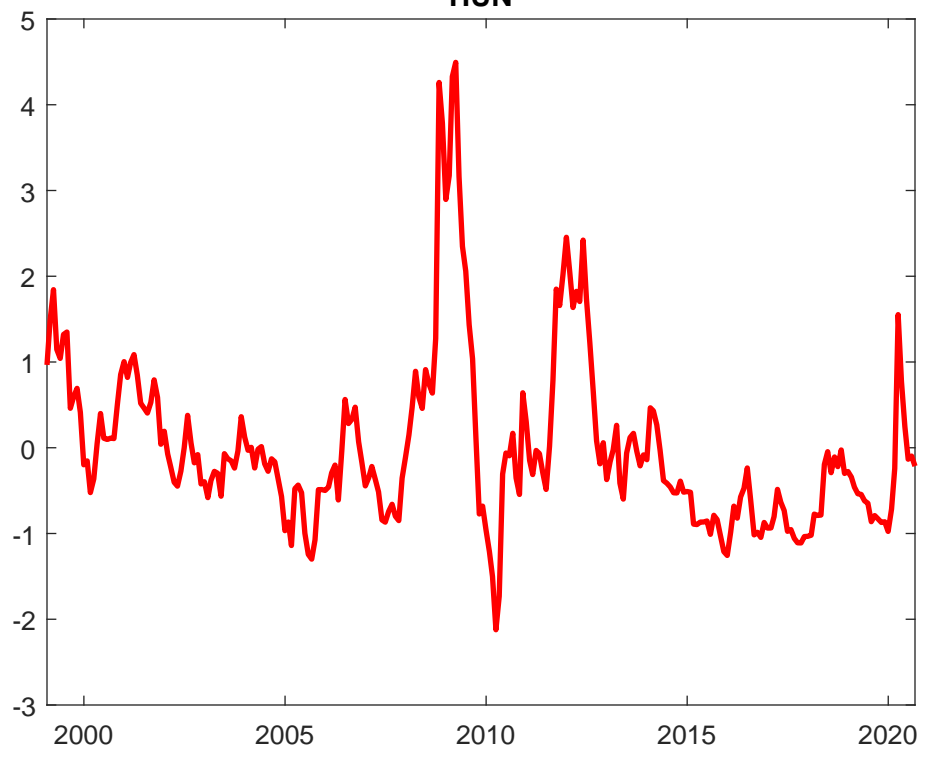
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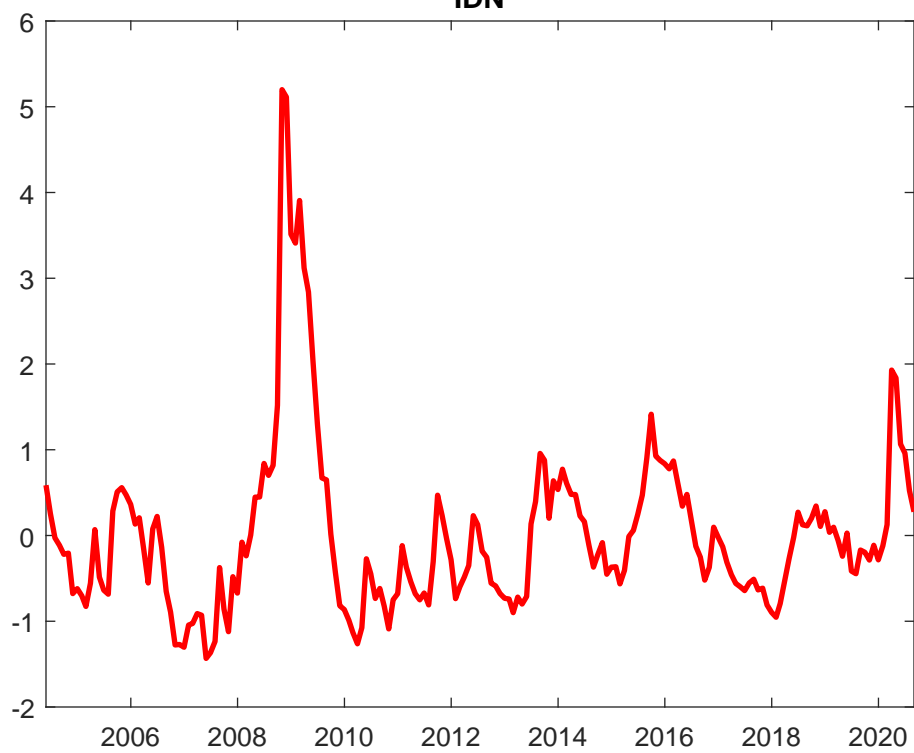
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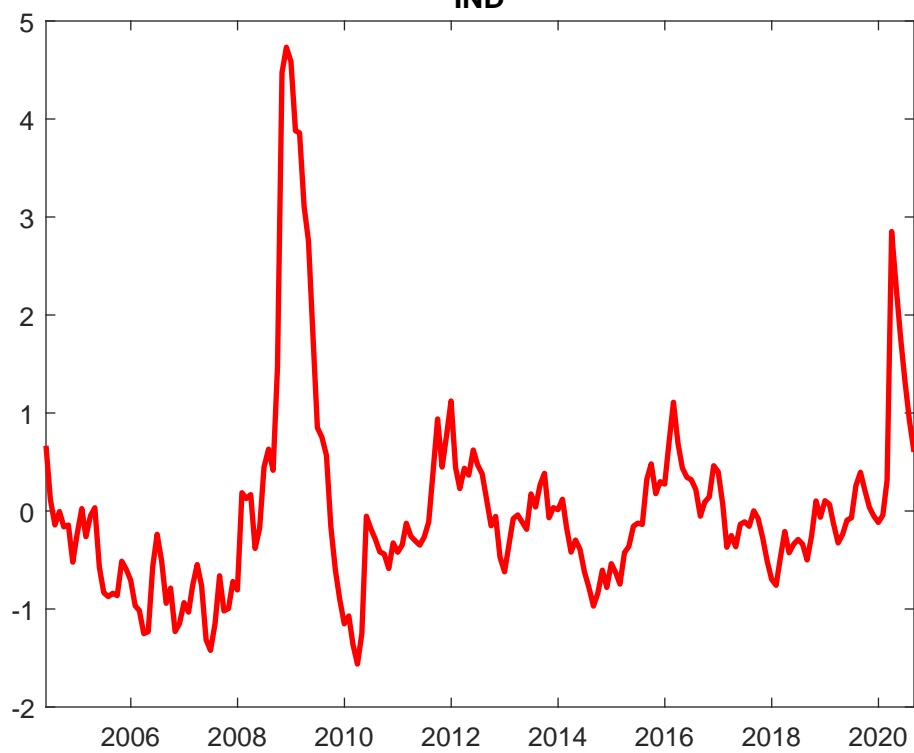
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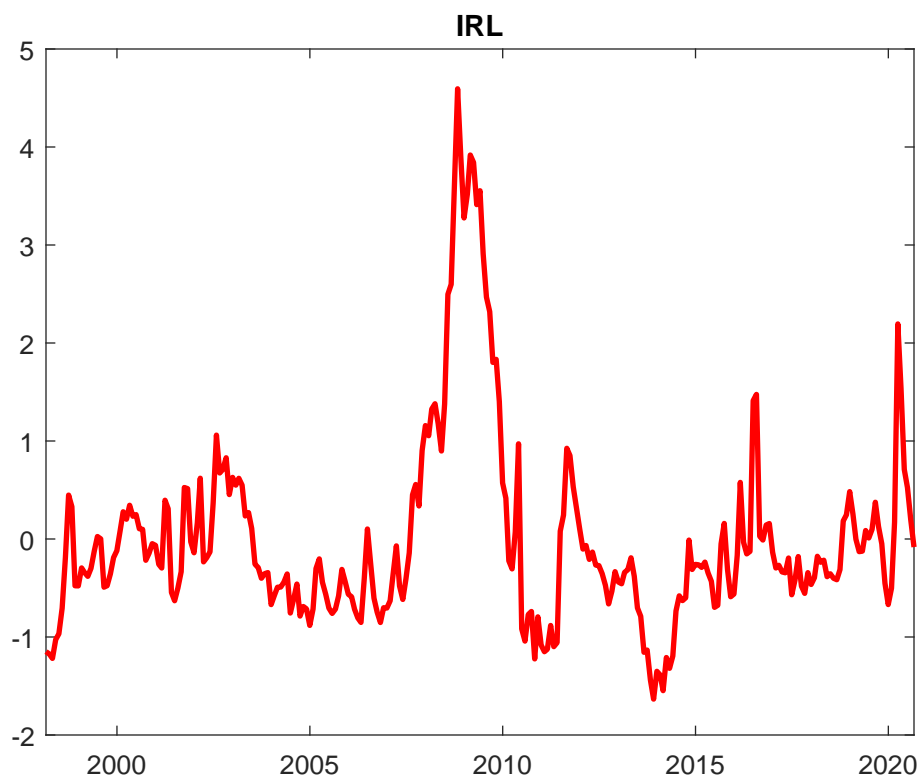


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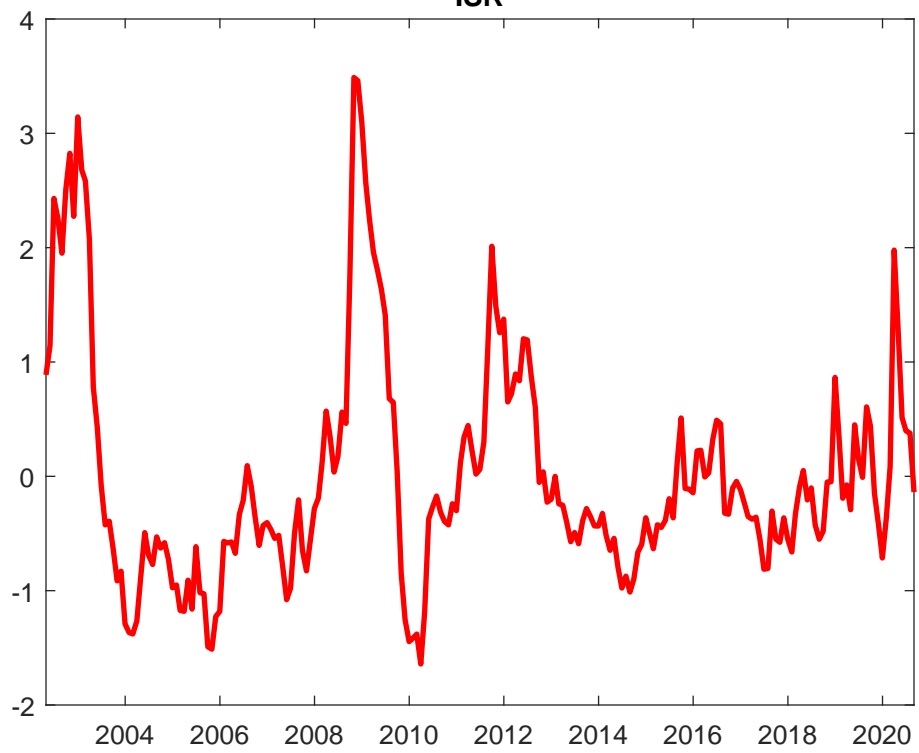


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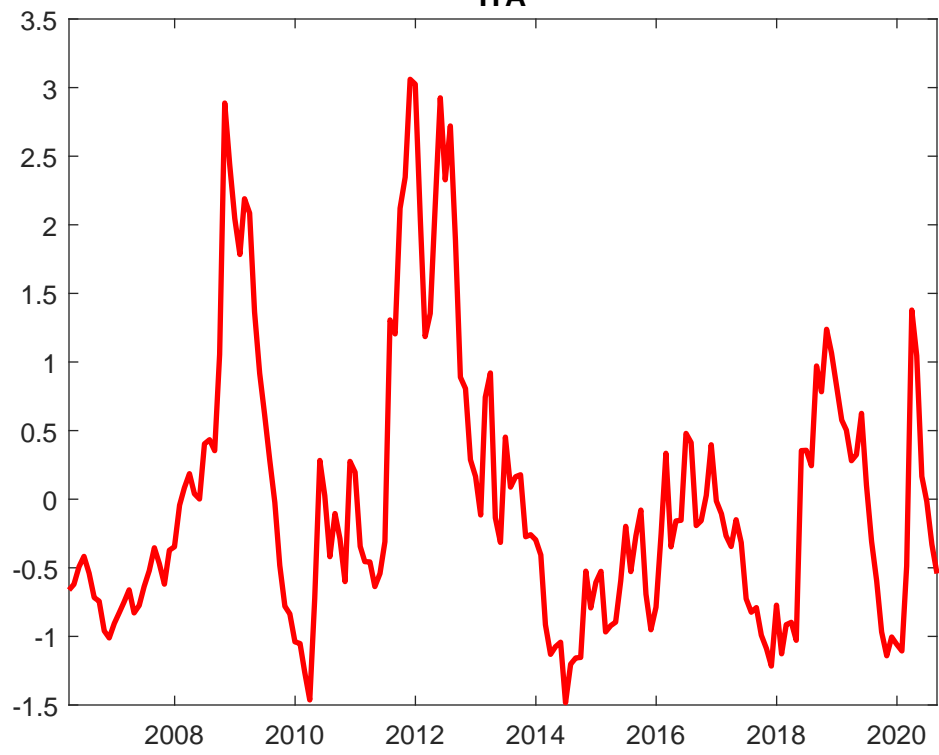


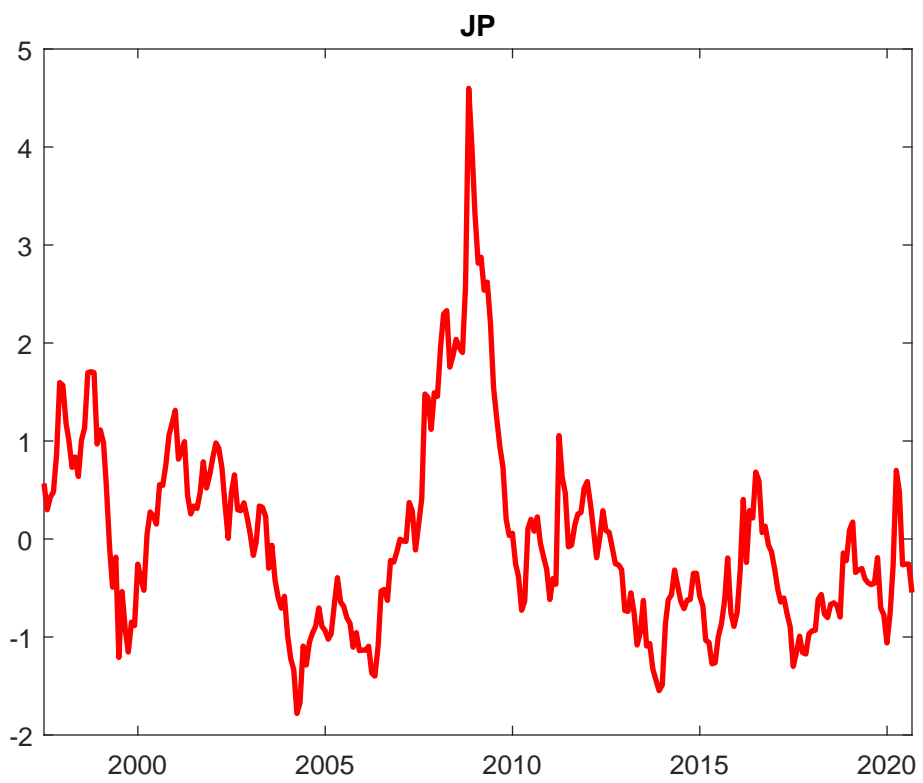


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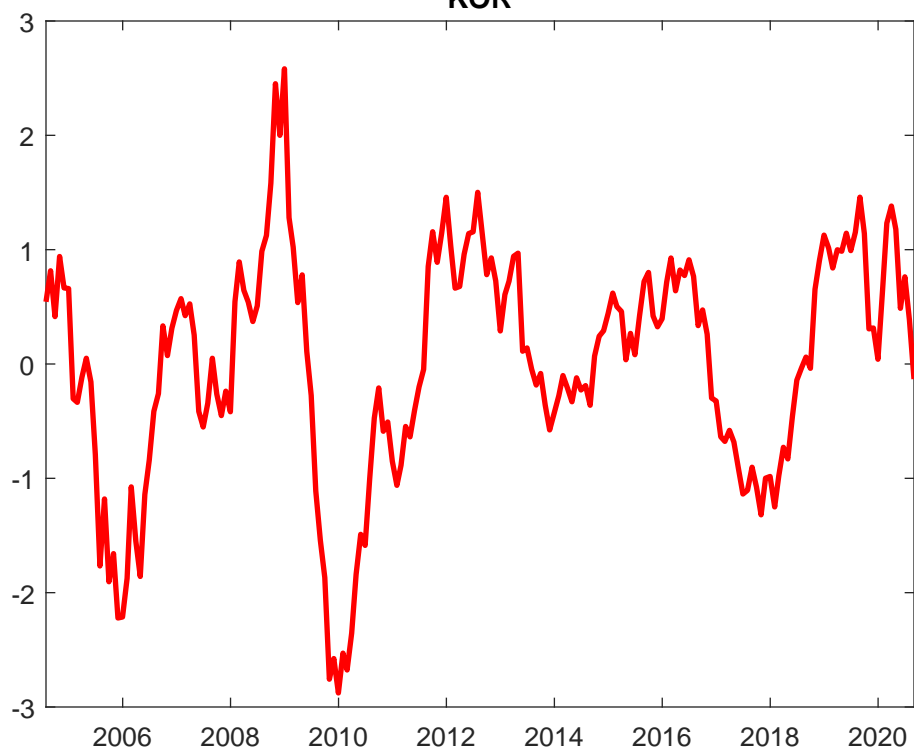


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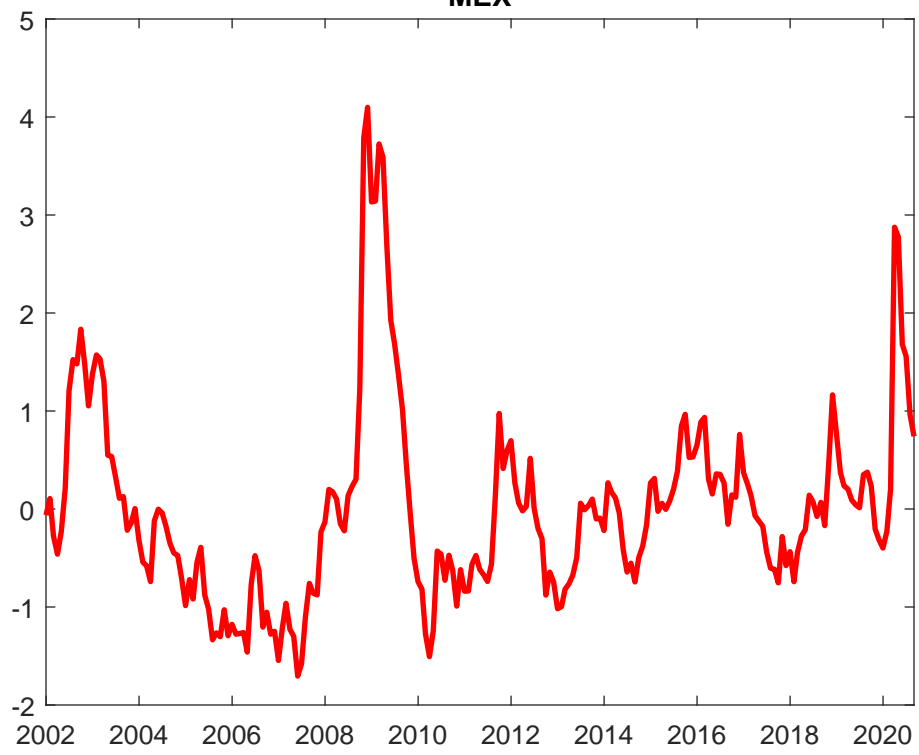




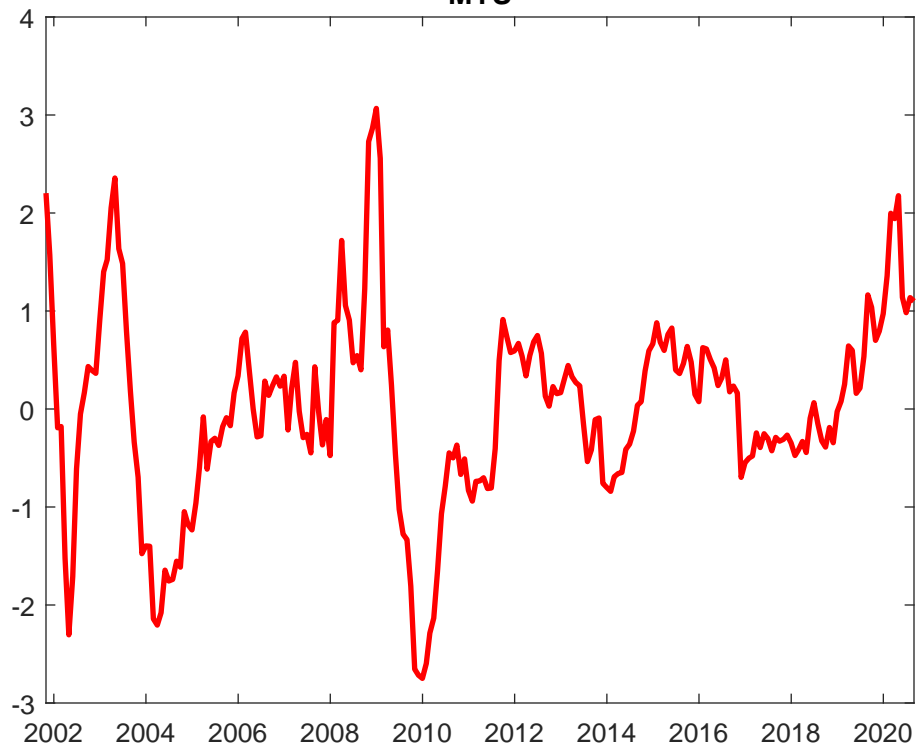
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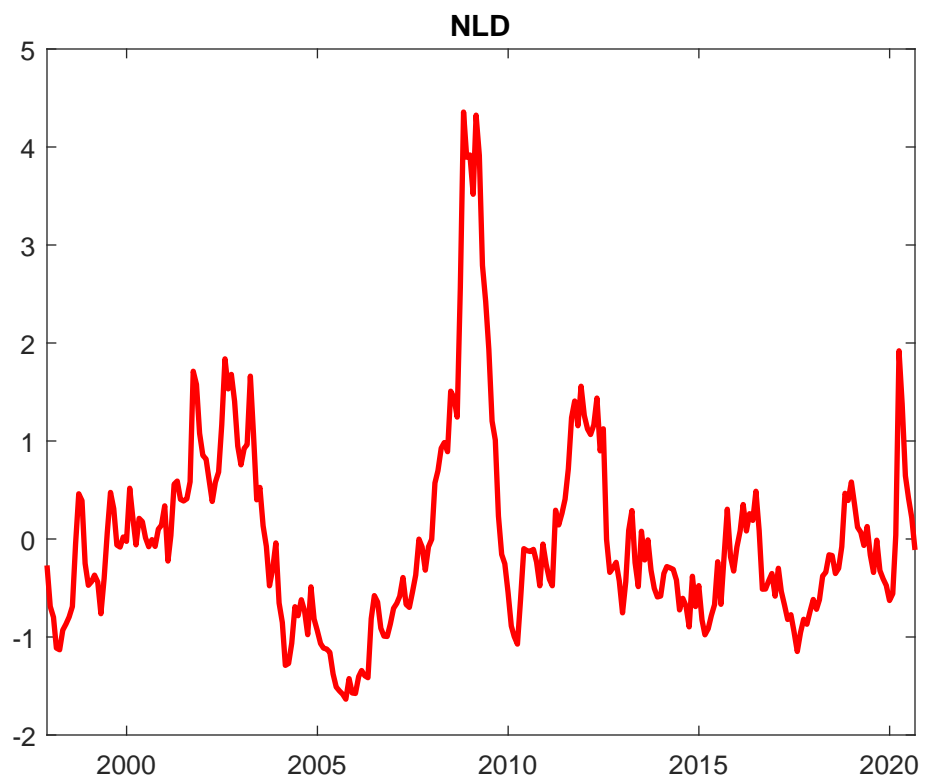


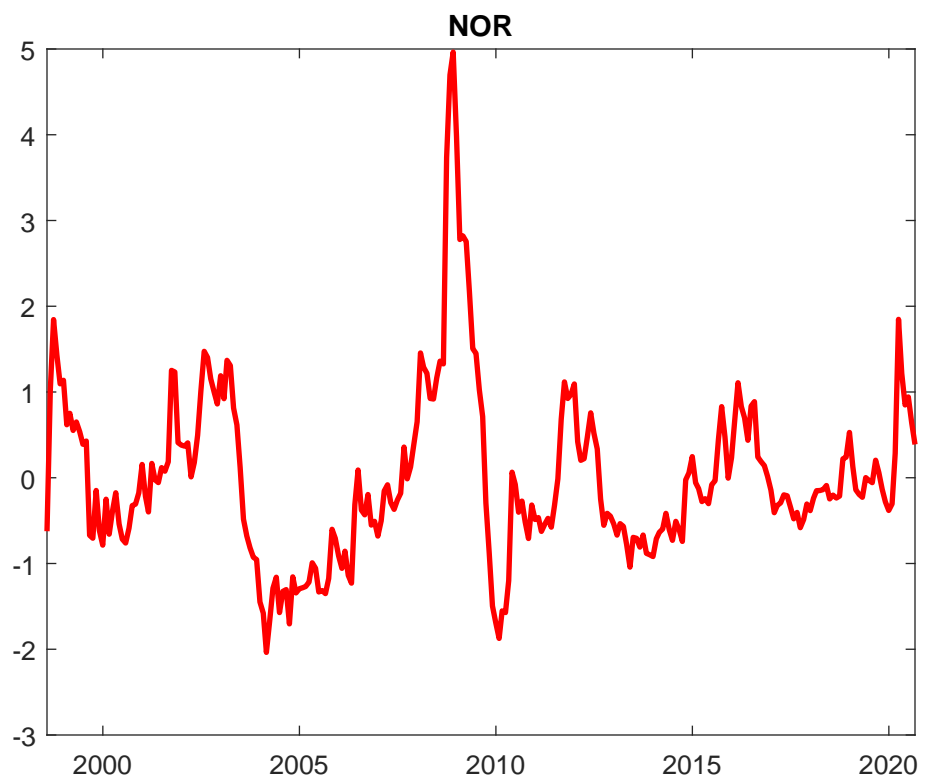
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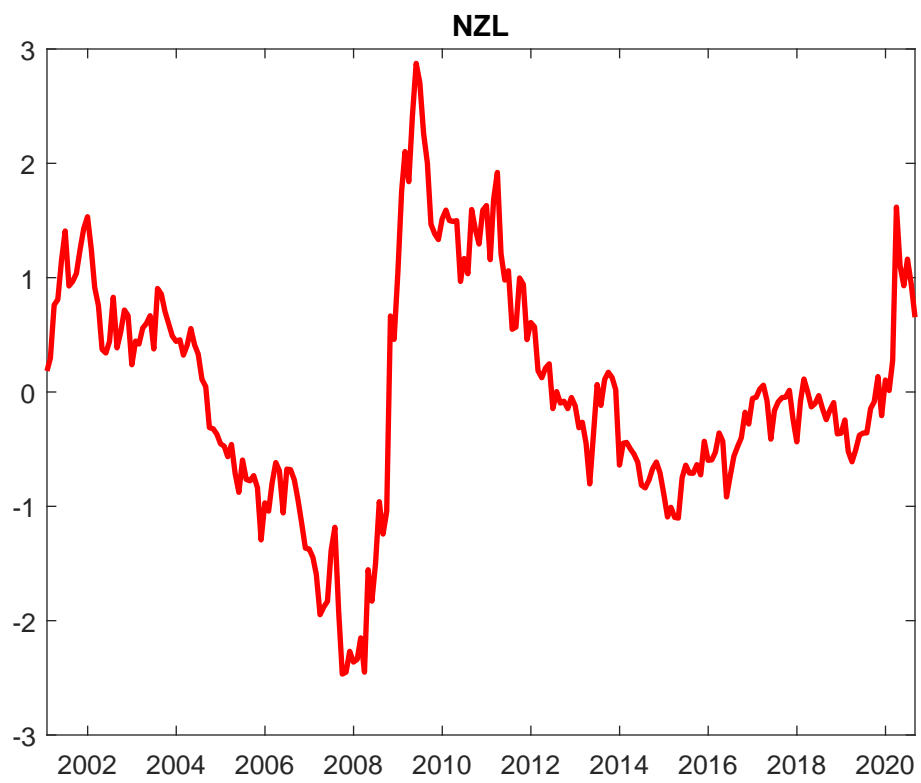


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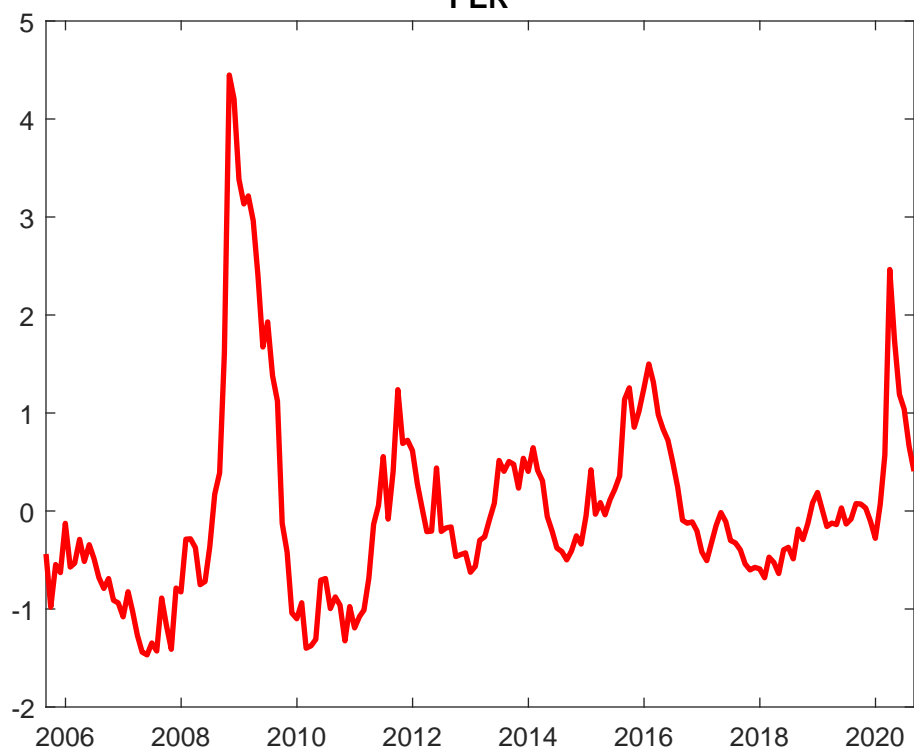




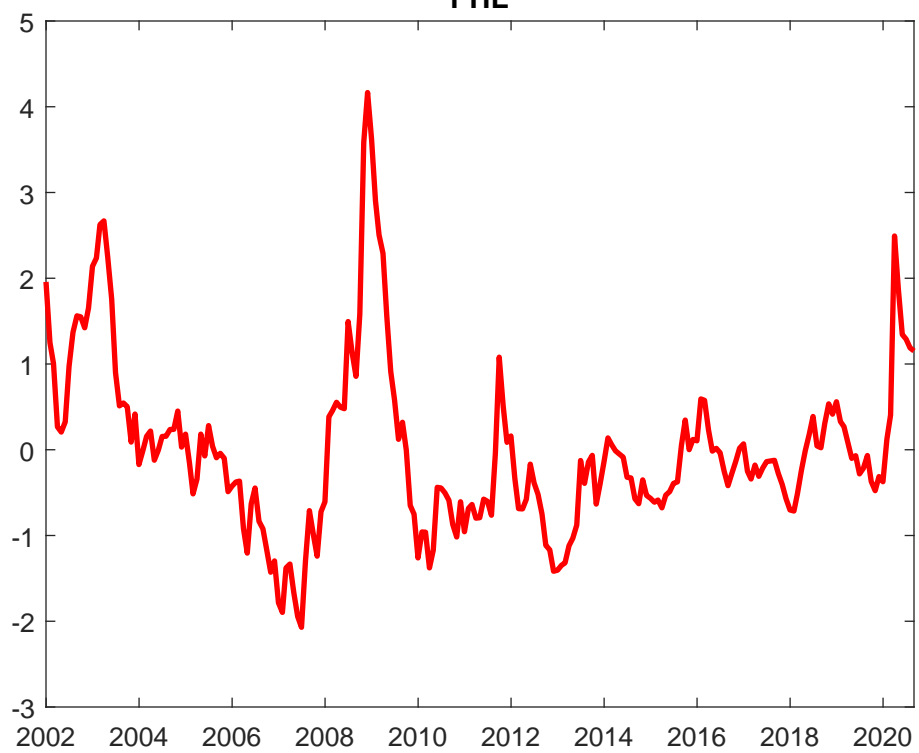




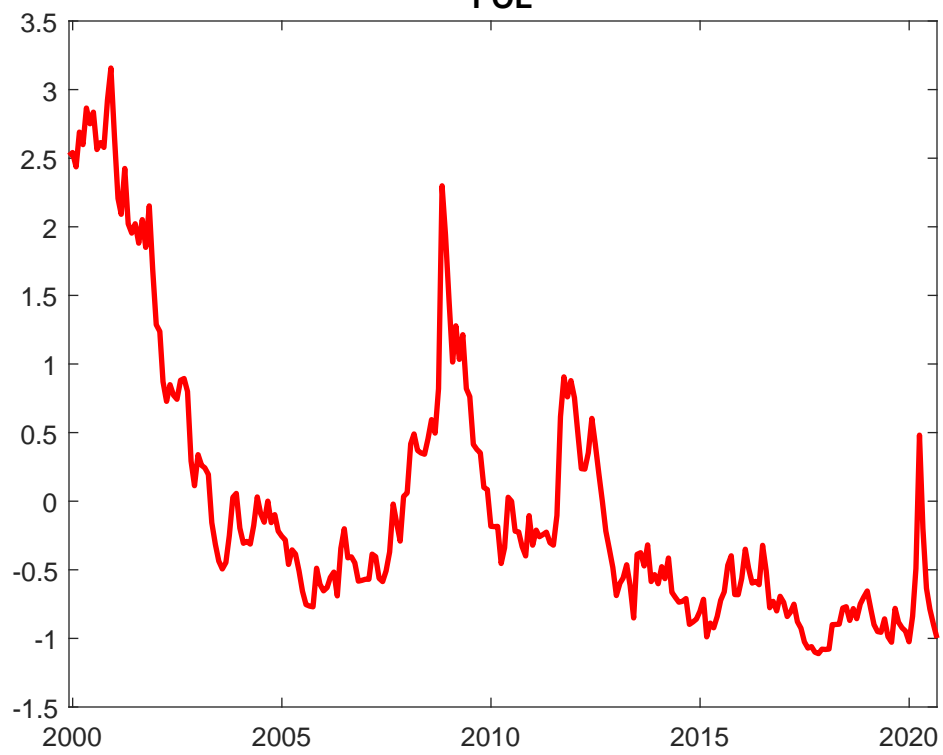
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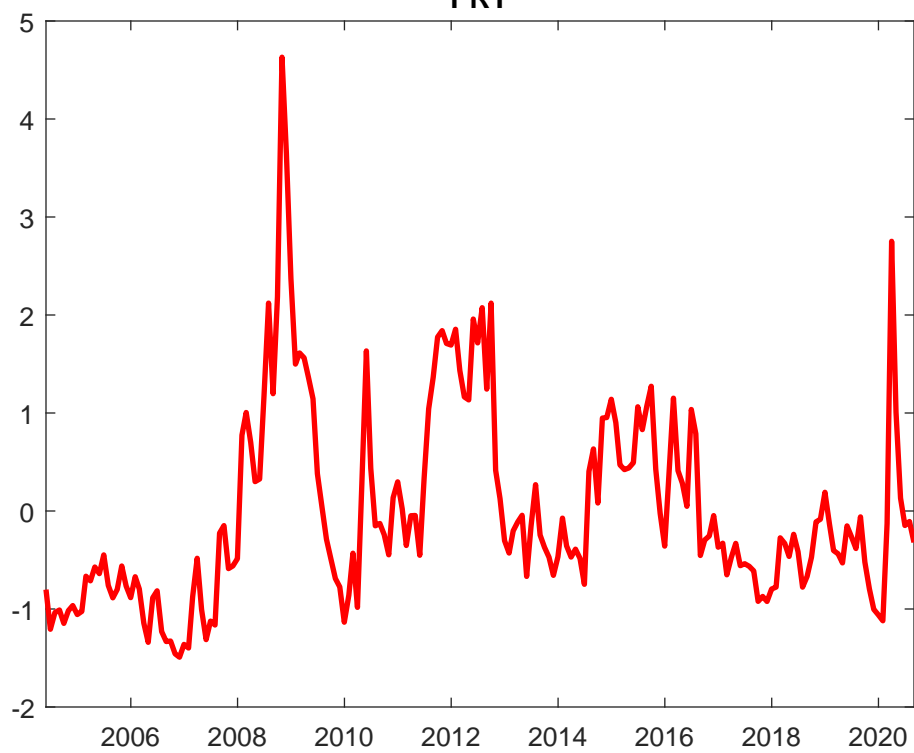
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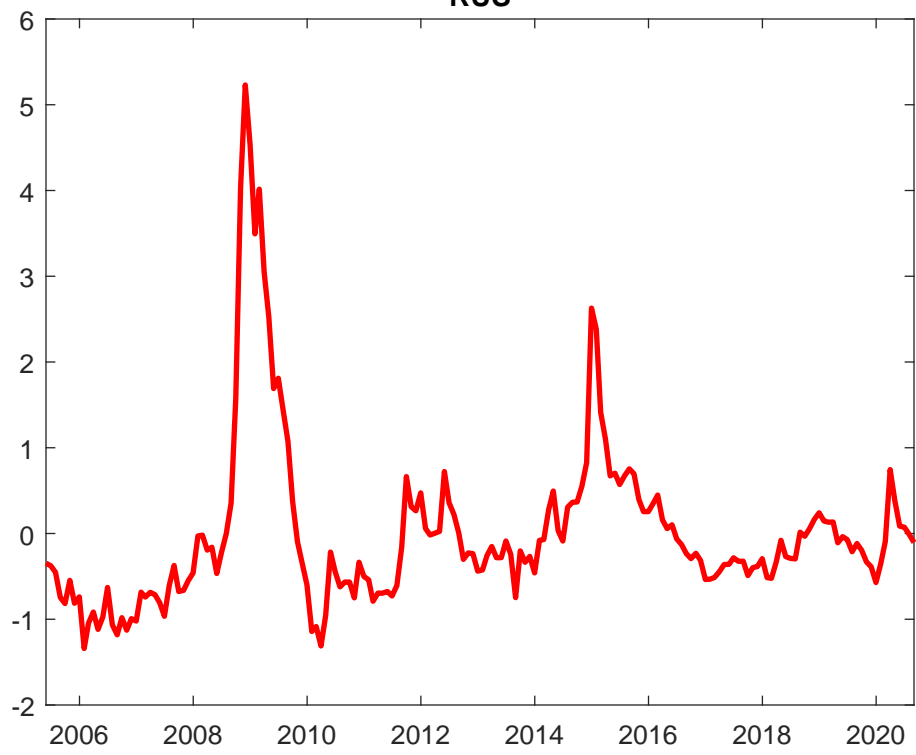
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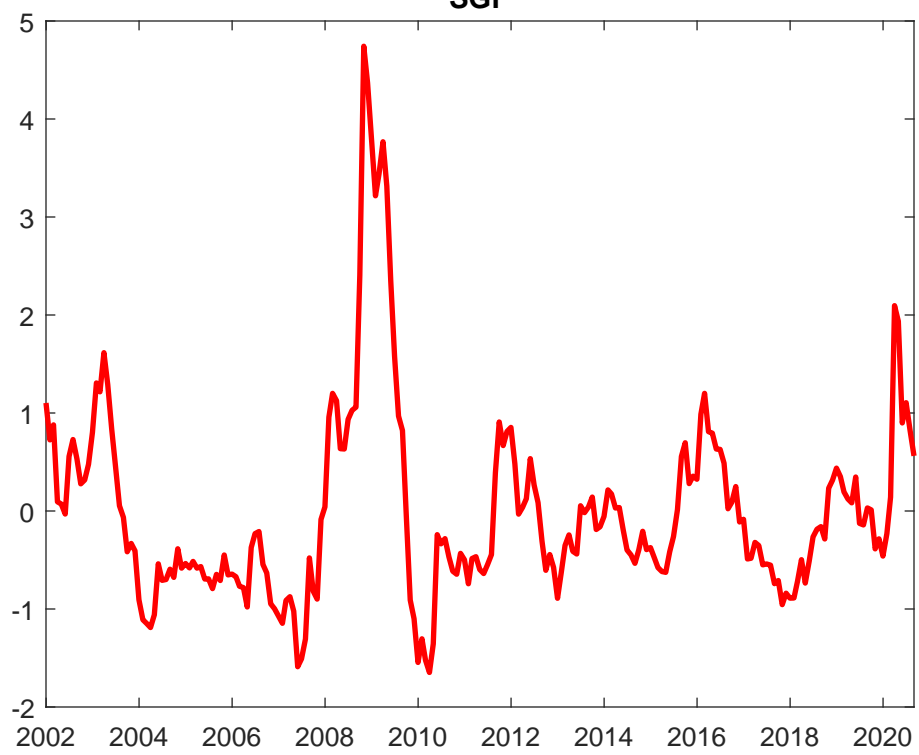
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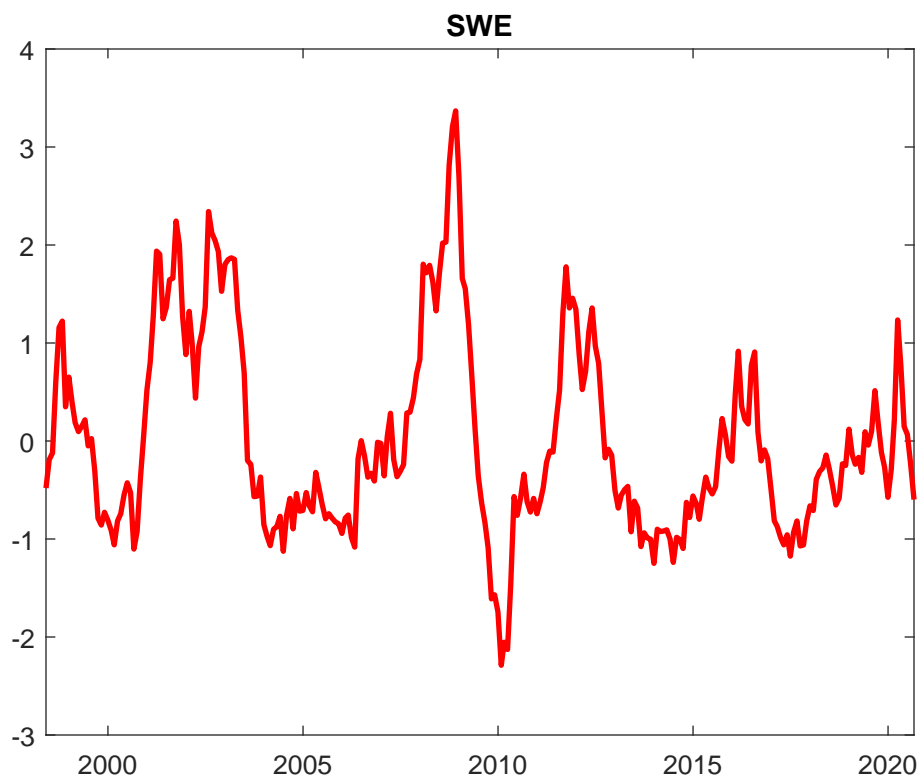


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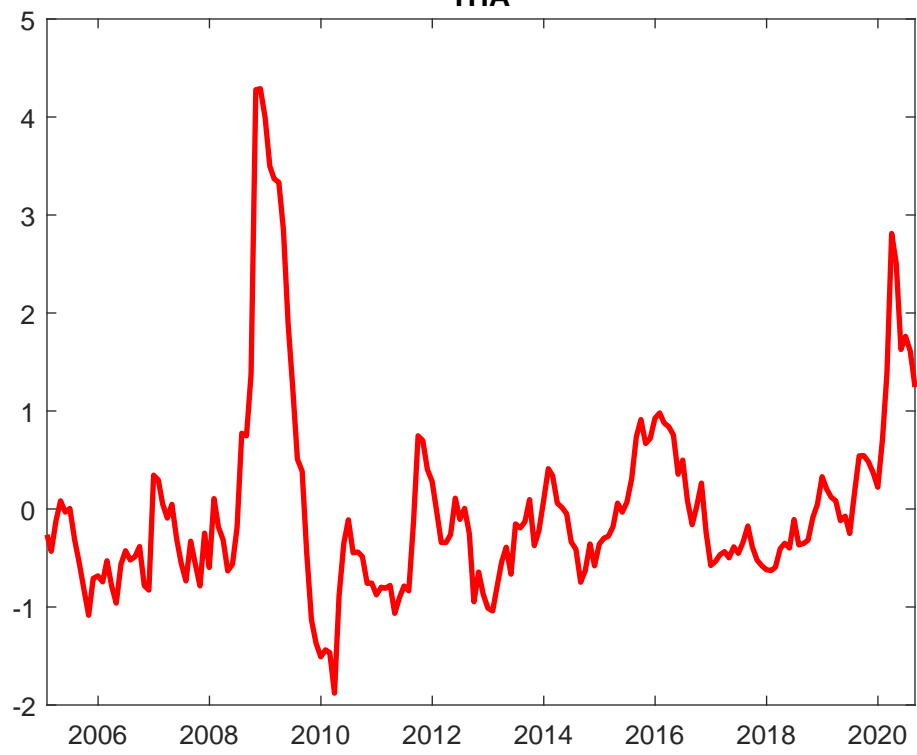


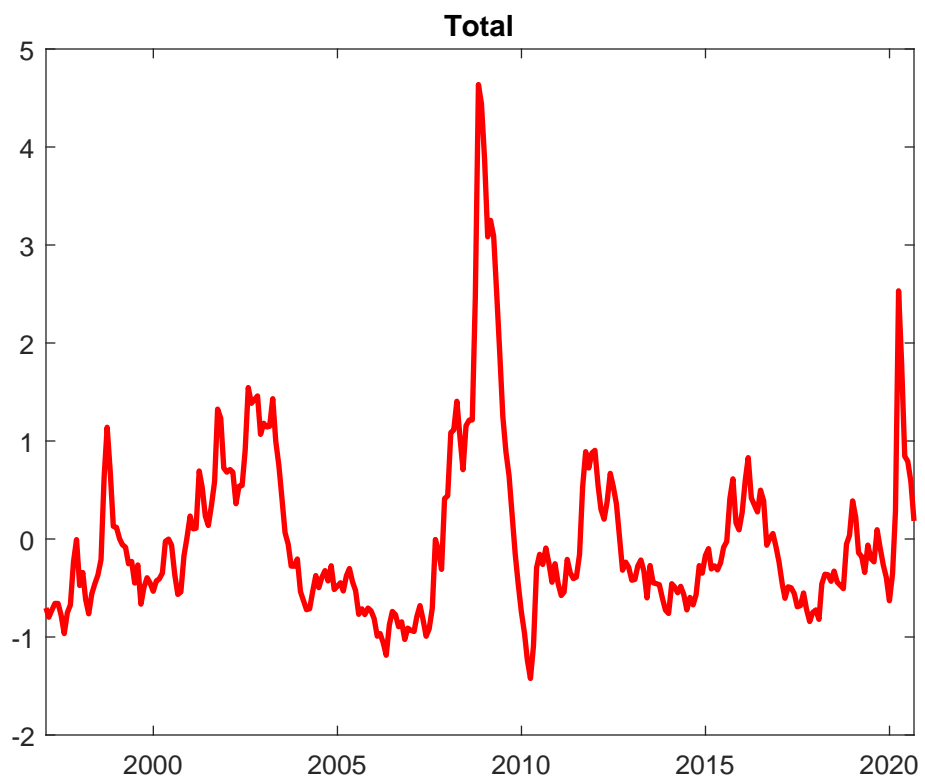
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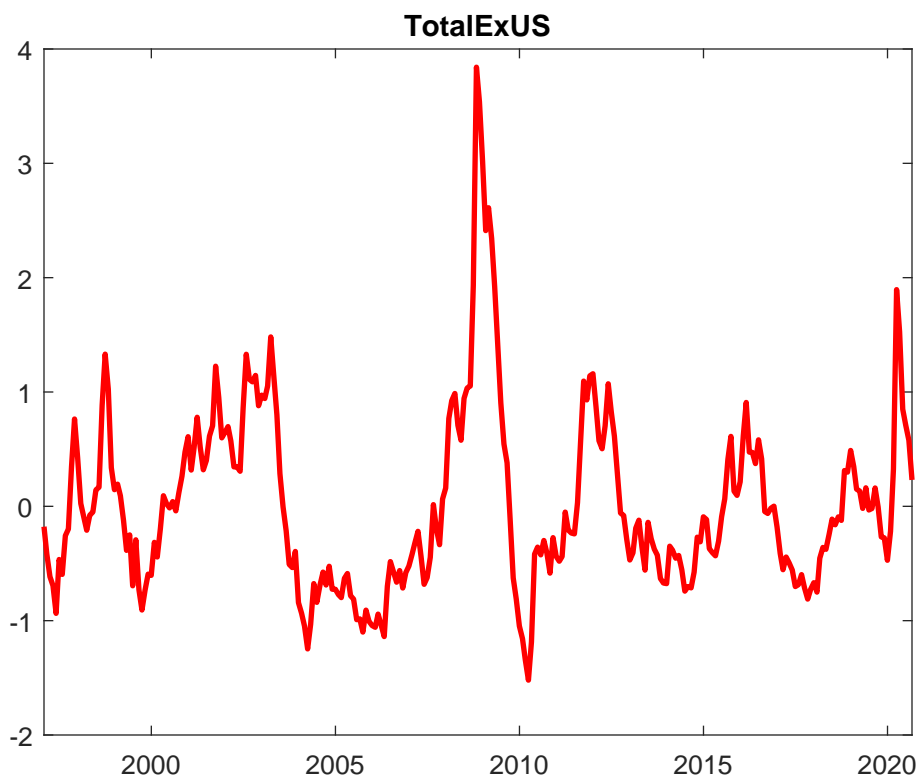


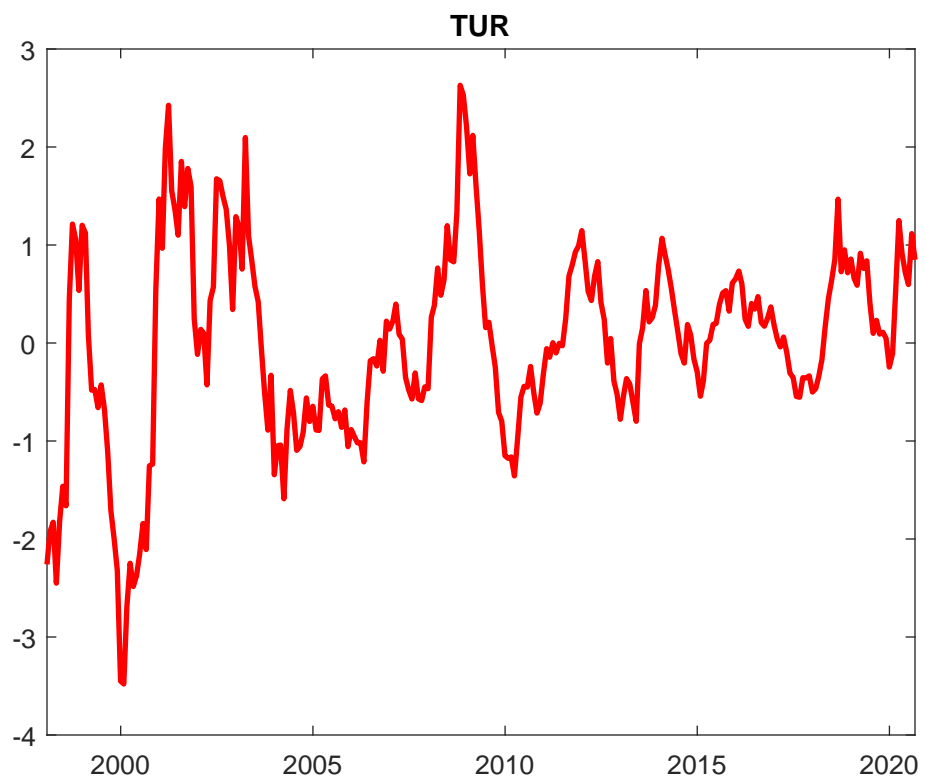


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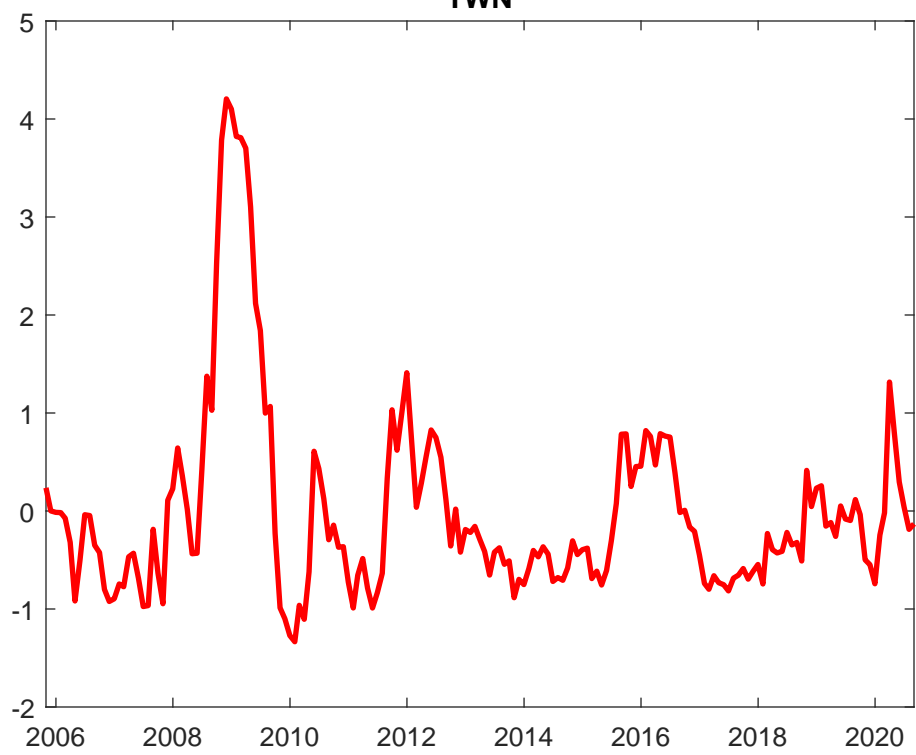




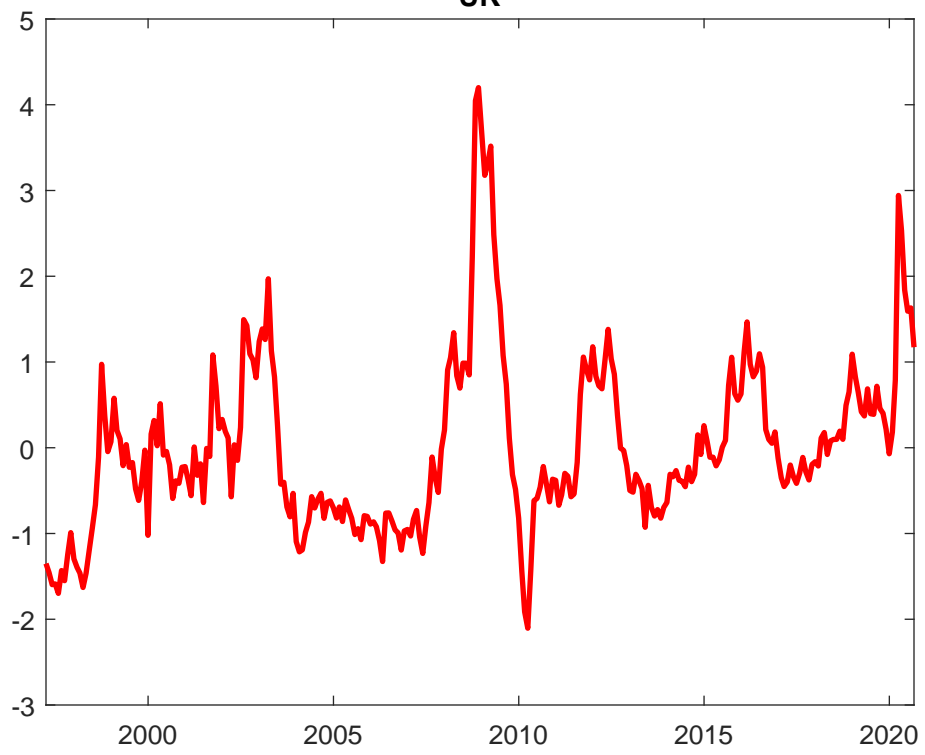


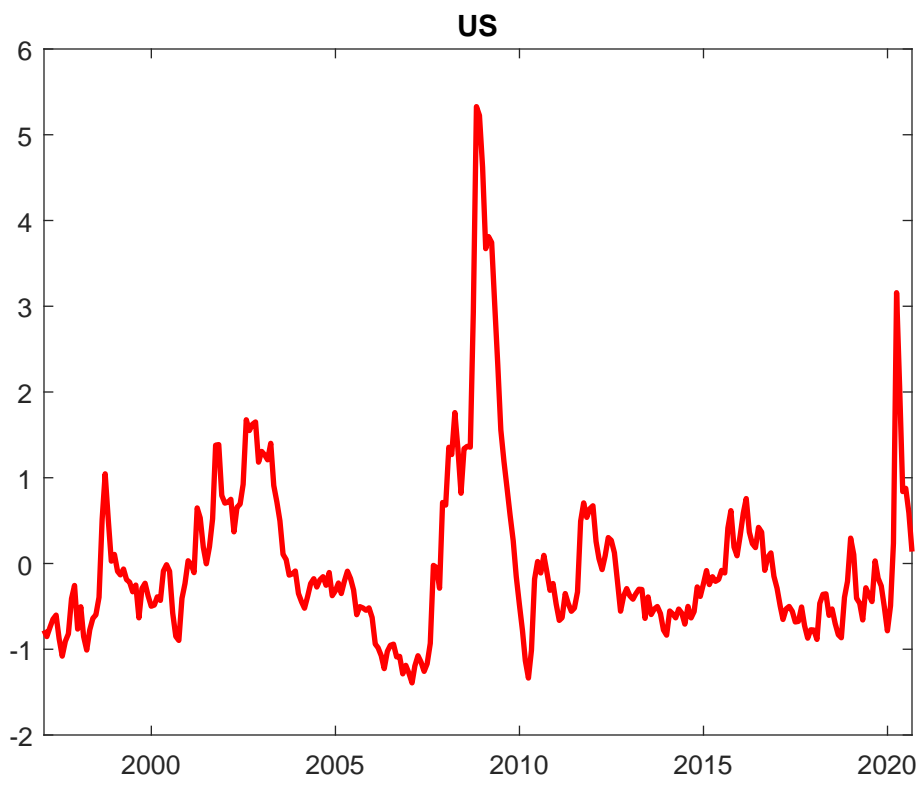


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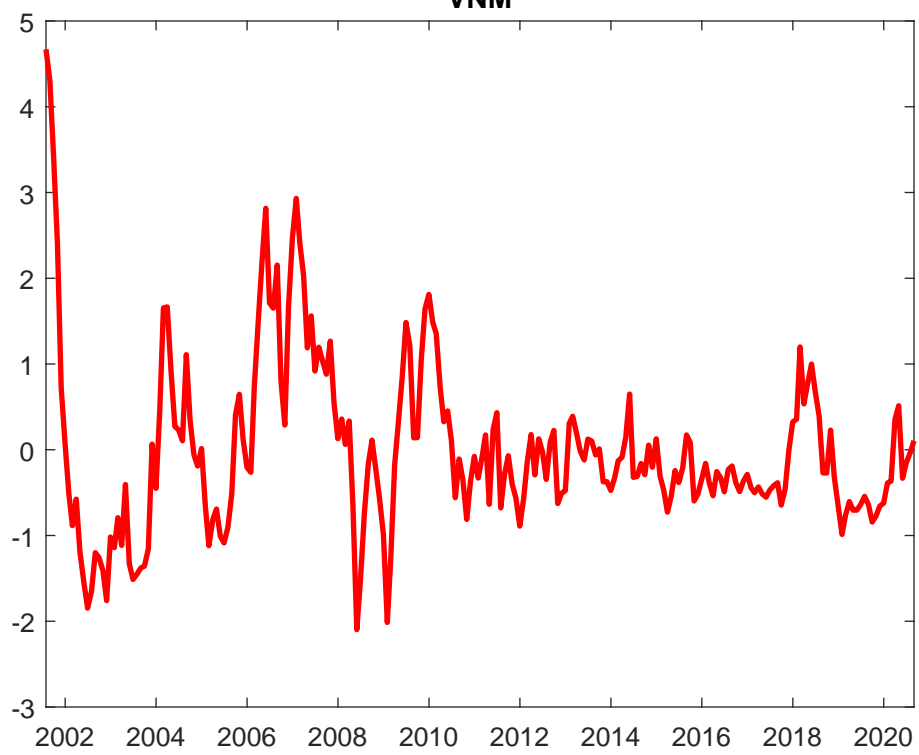


UK





VNM



ZAF

