CATÓLICA LISBON
BUSINESS & ECONOMICS

UNIVERSITÀ DEGLI STUDI DI NAPOLI FEDERICO II

The Effect of Financial Conditions on the Distribution of GDP growth

Giuseppe Ranieri

Dissertation written under the supervision of Joana Silva

Dissertation submitted in partial fulfilment of requirements for the MSc in Economics, at Universidade Católica Portuguesa and for the MSc in Economics & Finance at Università degli Studi di Napoli Federico II, September 2023

The Effect of Financial Conditions on the Distribution of GDP growth

Giuseppe Ranieri

Abstract

This thesis explores the relationship between financial stability and economic growth in the United States, the Euro Zone, Argentina, Brazil, and India over the past two decades. A central component of this research involves the development of a Financial Conditions Index (FCI) for each of these economies. Through econometric estimation of real GDP growth's time-varying distribution over the study period, this research unveils the impact of tight financial conditions on economic growth. In this thesis, I demonstrate that financial conditions not only significantly influence average GDP growth but also shape its distribution over time. In fact, periods of tight financial conditions are associated with increased overall economic growth uncertainty and a higher likelihood of extreme negative realizations in economic growth. This thesis underscores the pivotal role of financial conditions in magnifying negative risks concerning economic growth, both within the sample and out of the sample. It emphasizes the unique dynamics between financial stability and economic growth, highlighting interesting implications for both theoretical macroeconomic models and policymaking.

Key Words: Financial Conditions, GDP growth.

The Effect of Financial Conditions on the Distribution of GDP growth

Giuseppe Ranieri

Resumo

Esta tese explora a relação entre a estabilidade financeira e o crescimento económico nos Estados Unidos, na Zona Euro, na Argentina, no Brasil e na Índia ao longo das últimas duas décadas. Uma componente central desta investigação envolve o desenvolvimento de um Índice de Condições Financeiras (ICF) para cada uma destas economias. Através da estimativa econométrica da distribuição variável no tempo do crescimento real do PIB durante o período de estudo, esta investigação revela o impacto de condições financeiras restritivas no crescimento económico. Nesta tese, demonstro que as condições financeiras não só influenciam significativamente o crescimento médio do PIB, como também moldam a sua distribuição ao longo do tempo. De facto, os períodos de condições financeiras restritivas estão associados a uma maior incerteza global do crescimento económico e a uma maior probabilidade de realizações negativas extremas no crescimento económico. Esta tese sublinha o papel central das condições financeiras na ampliação dos riscos negativos relativos ao crescimento económico, tanto dentro como fora da amostra. Salienta a dinâmica única entre a estabilidade financeira e o crescimento económico, destacando implicações interessantes tanto para os modelos macroeconómicos teóricos como para a definição de políticas.

Palavras-chave: Condições financeiras, crescimento do PIB.

Acknowledgments

I am deeply grateful to Professor Joana Silva for her invaluable guidance, unwavering support, and exceptional kindness throughout this semester. Working under her supervision has been an absolute privilege, and I am truly appreciative of the opportunity.

My sincere thanks also go to all my colleagues in the Master's program in Economics and Finance, who have been extraordinary friends and companions on this incredible experience, with a special mention to Gennaro, who has become a brotherly friend and my biggest supporter in this adventure in Lisbon.

I would like to express my gratitude to Vania for her unwavering support during this remarkable journey. I am incredibly grateful for the immense value of her encouragement to me.

Lastly, but certainly most importantly, I want to express my deepest gratitude to my family, particularly my mother Teresa and my grandmother Carmela. Their support and trust in me have been immeasurable throughout the years, and I am forever grateful for the opportunity they provided me to study at this esteemed institution.

Table of Contents

Table of Figures

Table of Tables

I. Introduction

The global economy has become increasingly complex and interdependent, which has made it more vulnerable to sudden and severe shocks. Policymakers are starting to recognize the need to consider downside risks when making policy decisions, given the potential impact of unexpected events like global pandemics, geopolitical tensions, and financial crises.

Econometric models often produce point estimates of the central tendency of the variable of interest, including the unconditional mean or median, but they typically overlook the risks surrounding the central forecast. This can result in an overly optimistic outlook for the economy, leading policymakers to make decisions based on too positive forecasts that could have negative consequences.

Therefore, policymakers must consider downside risks when making policy decisions to better protect the economy from potential shocks. This approach involves considering a range of scenarios that incorporate adverse events in addition to central forecasts, as well as using tools like stress tests to assess the resilience of the economy to unexpected shocks. By taking a more conservative approach that incorporates potential adverse scenarios, policymakers can make more informed decisions that better safeguard the economy from potential shocks.

This specific topic has been treated by Adrian, Boyarchenko, Giannone (2019) for the US, and in this thesis, my purpose is to replicate their work for several countries. The replication is carried out across diverse economies, encompassing both developed economies such as the US and Euro Zone, and developing economies like Argentina, Brazil, and India. Economists commonly recognize that developing countries have more unstable financial conditions. Consequently, my thesis seeks to illuminate the way financial instability in these countries has hindered economic growth.

However, replicating this study is not a straightforward task and involves a crucial preliminary step. In fact, there is currently no equivalent National Financial Conditions Index like the one developed by the FED to summarize the financial conditions of the US economy over time, available at an official level for the other countries. Hence, it becomes necessary to define and create such an index for these countries.

To accomplish this, I followed a three-step approach: First, I constructed several Financial Conditions Indexes for the US using different combinations of data and methodologies. Then, I selected the one that utilizes less private and sophisticated data while still exhibiting the highest capability to mimic and incorporate the trends of the official Financial Conditions Index constructed by the Fed in the past by maximizing the in and out-of-sample correlation of the constructed indexes with the official NFCI. Finally, using the same kind of data and weights utilized in the US FCI construction, I created comparable indexes for all the other countries.

Once I estimate a proper measure to assess financial conditions in the analysed countries, I proceed aligned with the work of the original authors. In particular, I model the real GDP growth distributions over time using past financial and economic conditions as regressors for all the countries mentioned above and use both variables with a lag of one quarter or of one year alternatively. To accomplish this result, I proceed by estimating the distribution semi-parametrically using quantile regressions to explore the different quantiles of GDP growth considering both economic and financial conditions as regressors. As a result, past financial conditions appear to influence more heavily the current real GDP growth for realizations in the lower quantiles, whether the upper quantiles do not present relevant fluctuations over time. I also show that, on one hand, past economic conditions are able to forecast relatively well the median of the distribution of GDP growth, but on the other hand, they lack relevant information on the remaining quantiles of the distribution.

I subsequently employ interpolation using the skewed t-distribution developed by Azzalini and Della Valle (2003), to smooth the estimated quantile distribution for each quarter, using four parameters (location, scale, shape, skewness) throughout a maximum likelihood estimation.

The empirical quantile distribution is then converted into an estimated conditional distribution of GDP growth, visually presented in Figure 9. In line with the authors, I find that the entire distribution, and not just the central tendency, evolves over time, with recessions associated with distributions with a strong skewness on the left and expansions associated with distributions that are closer to being symmetric. Moreover, the probability distributions preserve the stability of the right tail from the estimated quantile distribution, whereas the median and left tails of the distribution show sharper variations in the time series. This difference in the distribution of future GDP growth indicates that the likelihood of negative growth fluctuates more over time compared to the likelihood of positive growth, when considering financial conditions.

In addition, I inspect different definitions of the risks, both of upside and downside, surrounding the central GDP growth forecast by using two metrics. The first metric is defined as the entropy, divided into the upside and downside entropy, whether the second metric is represented by the expected short-fall and its upper tail counterpart, known as expected long-rise.

The downside entropy metric captures how much the downside risks computed on the conditional[1] distribution exceeds the downside risks predicted by the unconditional[2] distribution. It provides insight into the level of risk that the economy faces in case of adverse events. On the other hand, the expected short-fall metric measures the total probability that the conditional distribution assigns to a particular section of the left tail of the distribution. This helps to quantify the expected loss that could be incurred due to unfavourable financial conditions. Conversely, the upside relative entropy metric captures the excess upside risk predicted by the conditional distribution with respect to the one predicted by the unconditional one. It provides insight into the level of risk that the economy faces in the event of positive economic events. The expected long-rise metric measures the total probability that the conditional distribution assigns to a particular section of the right tail of the distribution. This helps to quantify the expected gain that could be achieved due to favourable financial conditions.

This thesis highlights the relationship between financial conditions and measures of downside risk in the analysed countries. It reveals that both the presented measures of downside risk are influenced by financial conditions, while measures of upside risk tend to be more stable over time. This asymmetry aligns with the authors' findings for the US, indicating that the impact of current financial conditions on future GDP growth is notably stronger for lower quantiles of the distribution compared to upper quantiles.

Furthermore, my examination of developing economies has highlighted the significance of this connection within these nations. In their distinctive contexts, particularly in the case of Argentina, this interrelation plays a central role in shaping growth trajectories, especially during periods of financial instability marked by increased uncertainty surrounding GDP growth

[1] The conditional distribution refers to the distribution of GDP growth estimated using the lagged GDP growth and the constructed Financial Condition Index as regressors. This is estimated twice including a one-year lag and one quarter lag for both the variable separately.

[2] The unconditional distribution refers to the distribution of GDP growth estimated using only the lagged GDP growth as regressor. This is estimated twice including a one-year lag and one quarter lag separately.

outcomes. These dynamics amplify the probability of recessions in a more accentuated manner, further underscoring their pivotal contribution to the economic growth of these developing nations.

In addition, I examine how well the financial conditions can forecast GDP growth out-of-sample, both for the upcoming quarter and the next year. To accomplish this, I initially generate in-sample predictions using data from the beginning of the different countries' datasets[3] to the end of 2012, and then recursively calculate out-of-sample predictions only one period ahead, simulating the actions of a real economist making predictions with up-to-date information. These evaluations are valuable in verifying the reliability of the predictive distributions and their capacity to accurately identify potential risks that could negatively impact GDP growth.

The evidence of the importance of financial conditions in predicting GDP growth risks is extensively discussed for all the analyzed countries, especially for developing economies with a more uncertain growth path.

The thesis proceeds as follows. Section 2 presents the literature background of the work. Section 3 introduces the data and the methodology used in estimating the Financial Conditions Index (FCI). Section 4 focuses on the Econometric Model for Conditional GDP growth distribution estimation and the main findings. Section 5 concludes including the theoretical and monetary policy implications of these findings.

[3] Which are different across the different countries. In particular:
Country: US. Timespan: 1993.Q1 - 2022.Q4. Frequency: Quarterly.
Country: Euro Zone. Timespan: 2003.Q1 - 2022.Q4. Frequency: Quarterly.
Country: Argentina. Timespan: 2004.Q2 - 2022.Q4. Frequency: Quarterly.
Country: Brazil. Timespan: 2004.Q1 - 2022.Q4. Frequency: Quarterly.
Country: India. Timespan: 2002.Q1 - 2022.Q4. Frequency: Quarterly.

II. Background

Central banks and governments have been concerned about financial conditions for many years, but the specific nature and focus of those concerns have evolved over time. One of the earliest examples of central banks worrying about financial conditions can be traced back to the 19th century. During this time, central banks such as the Bank of England and the Federal Reserve were primarily focused on maintaining the convertibility of their currencies to gold. As such, they were often preoccupied with managing the supply of money and credit to maintain stable exchange rates and prevent financial crises.

In the 20th century, the focus of central banks and governments shifted to broader macroeconomic objectives such as stabilizing inflation and promoting full employment. With this shift came an increased focus on financial conditions as a primary driver of economic activity. Central banks began to pay closer attention to interest rates, credit availability, and other financial indicators to understand the overall state of the economy and make informed policy decisions. The importance of financial conditions was further underscored by a series of financial crises in the latter half of the 20th century, including the 1970s oil crisis and, more importantly, the 2007-2008 global financial crisis, triggered by the Subprime mortgages bubble which led to the collapse of Lehman Brothers and one of the deepest global recessions since Great Depression. These events demonstrated the potential for financial conditions to have a significant impact on the broader economy and highlighted the need for policymakers to monitor and manage financial risks. Today, central banks and governments continue to closely monitor financial conditions as part of their broader efforts to promote macroeconomic stability and financial resilience.

This continuous evolution of central banks approach toward financial stability as a key objective, led the Federal Reserve (Fed) in 1971 to construct a financial indicator able to capture on a weekly basis the overall financial conditions in US. The construction of this index opened a long track of works related to how summarize the financial conditions of a country or a region in an index able to properly explain the real solidity of financial conditions and how these conditions can affect the real economy.

1. Financial Conditions Index Constructions

Starting from the literature on Financial Conditions Indexes, is it important to understand which variables are generally important in designating the financial solidity of a country.

Interest rates play a key role in the discussion, in particular, these have a significant impact on financial conditions, as higher interest rates can increase borrowing costs, reduce economic activity, and tighten financial conditions, while lower interest rates can have the opposite effect. This was noted by Bernanke and Gertler (1989) who examined the impact of monetary policy on the economy. Stock prices are also seen as a key indicator of financial conditions, with rising stock prices indicating optimism among investors and relatively loose financial conditions. In contrast, falling stock prices can signal pessimism and a deterioration of financial conditions. This was observed by Kuttner and Posen (2001), who examined the relationship between stock prices and monetary policy. Credit spreads, or the difference in yield between different types of bonds, are another important factor influencing financial conditions. When credit spreads are widening, it can signal that investors are becoming more risk-averse, which can tighten financial conditions, as noted by Holton and D'Acri (2018) in their analysis of credit spreads and financial conditions. Exchange rates can also have an impact on financial conditions, particularly in export-dependent countries. A stronger currency can make exports more expensive, reducing demand and worsening financial conditions, while a weaker currency can have the opposite effect. This was discussed by Forbes and Warnock (2012), who examined the impact of exchange rates on financial conditions. Finally, the level of money supply can also influence financial conditions, with a high level of money in circulation making it easier for businesses and households to borrow and spend, which can loosen financial conditions. In contrast, a tight money supply can make borrowing and spending more difficult, which can deteriorate financial conditions. This was discussed by Mishkin (1995), who examined the impact of the money supply on financial conditions.

Then, many authors proposed several methodologies to incorporates all those interesting variables in a unique measure capable of signalling the financial solidity of a country, starting from the NFCI constructed by the FED, a weighted average of 105 metrics has been used. The use of Principal Component Analysis, allows the variables to be weighted based on their contribution to the overall variation in financial conditions, remains the dominant methodology in literature since it does not involve estimation errors, and it is used in several ECB working papers.

Anyway, many scholars and banks have constructed FCIs using different methods, such as factor analysis or regression analysis. Moreover, recent authors developed more sophisticated ways to summarize a wide set of variables in a more efficient and accurate way as Montagnoli at al. (2005), which constructed a methodology capable of having time varying weights in the Financial Condition Index construction. As this topic is highly explored in literature by scholars, the construction of a proper index for financial conditions plays a crucial role in private banks management and for this reason many large banks proposed own indexes for the assessment of overall economies financial conditions, as: Goldman Sachs, JP Morgan Chase, or Citigroup. As an example, Goldman Sachs Financial Conditions Index uses a weighted average of 18 financial variables, including interest rates, stock prices, and exchange rates, that are chosen based on their statistical significance in predicting economic activity.

2. Financial Conditions Indexes Applications

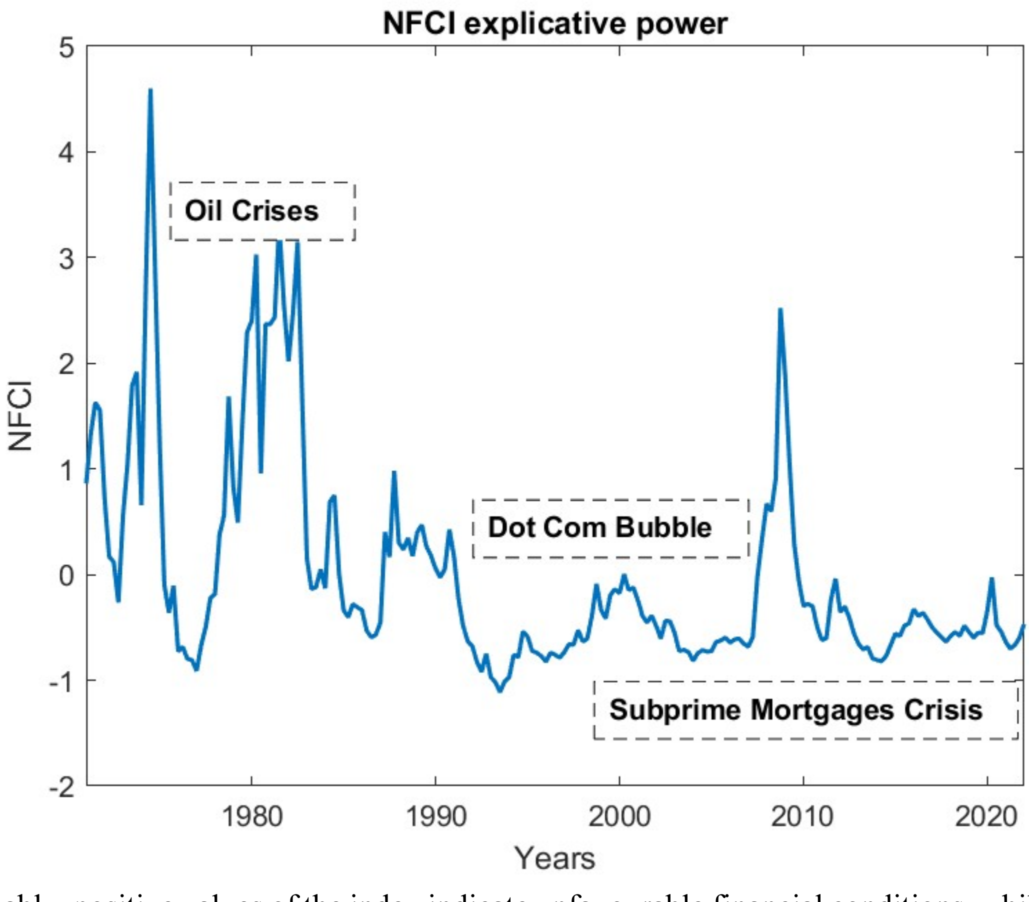
These indexes constructed using different methodologies and data have found many kinds of applications in several areas during the years. The most common use of Financial Conditions Indexes is in monetary policy analysis. Central banks can utilize the FCI to monitor the financial conditions of an economy and make more informed decisions regarding monetary policy. Another application of the FCI is in forecasting economic activity. Researchers have found that a simple FCI that considers interest rates, stock prices, and exchange rates can be utilized to forecast real GDP growth and inflation, as highlighted by a study conducted by Hatzius et al. (2010) in US. Moreover, the FCIs can be utilized to assess financial stability and identify potential vulnerabilities in the financial system. For example, Adrian and Shin (2010) employed an FCI that incorporated several financial indicators to detect periods of elevated financial stress and assess the potential for systemic risk. Finally, the FCIs can also be employed to compare financial conditions across countries. Kuttner and Shim (2012) constructed FCIs for several advanced economies and found that financial conditions were highly correlated across countries, suggesting that global factors played a critical role in determining financial conditions as globalization accelerates.

In this thesis, closely following the work done by Adrian et al. (2019) for the US, I estimate how the Financial Conditions can generate GDP vulnerabilities, affecting the overall GDP growth distribution, focusing more on its higher moments, as its variability, skewness, and tails ‘structure. In the following section, I will show in detail how I constructed an efficient Financial Conditions Index for the US for the period going from the beginning of 1993 to the end of 2022 (120 observation), able to efficiently replicate the official US NFCI by the Federal Reserve and then I replicate this index for a wide range of countries as: Euro Zone, Argentina, Brazil, and India.

III. FCI Construction: Data & Methodology

To fulfil the primary purpose of highlighting the growth vulnerabilities resulting from financial instabilities across a diverse set of countries, it is crucial to develop an appropriate index capable of capturing the general financial trends within an economy. To this end, I begin by endeavouring to replicate the National Financial Conditions Index for the United States, which has been meticulously constructed by the Federal Reserve. This index is meticulously crafted by taking a weighted average of 105 financial metrics, which are then normalized and adjusted to ensure they remain unaffected by economic activity and inflation dynamics. Through this robust approach, the NFCI has proven its reliability in capturing the dynamics of the nation's financial landscape. The effectiveness of the NFCI in presenting a comprehensive overview of the US economy's financial conditions is shown in Figure 1.

Figure 1. The explicative power of the NFCI by FED of US Financial Conditions
The panel shows the trend in the official US NFCI since its construction in 1971 and highlights how the index has been able to incorporate particularly severe financial crises over time.
Country: US. Timespan: 1971.Q2 - 2022.Q4. Frequency: Quarterly.



Notably, positive values of the index indicate unfavourable financial conditions, while negative values signify more favourable economic circumstances. High spikes in the index are particularly noteworthy, as they often signal severely adverse financial conditions.

However, replicating this index in a broader international context poses notable challenges due to its composition, which includes a substantial number of 105 metrics, several of which are not publicly accessible. This complexity raises concerns about the feasibility of extending the index to other countries. To address this issue, I adopt a systematic approach that involves several essential steps:

1. Constructing Multiple Financial Conditions Indexes for the US: Initially, I create several financial conditions indexes for the US, employing different sets of data and methodologies. These alternative indexes serve as a basis for identifying the most appropriate approach to replicate the US NFCI.

2. Selecting the Optimal Index: To determine the most effective index, I conduct a thorough analysis of each constructed index, evaluating their performance both within and outside the sample. By scrutinizing their in and out-of-sample correlations with the official US NFCI, I can identify the index that best captures the underlying financial conditions.

3. Replicating the Chosen Index for Other Countries: Once the optimal index for the US has been identified, I use the same weights and methodologies to construct a comparable Financial Conditions Index for each country under consideration. This process involves adapting the index to account for specific financial structures, economic conditions, and data availability in each country.

By following this approach, I generate an index that captures the nuances of financial instability in different countries. Subsequently, these constructed indexes will serve as valuable tools in emphasizing the critical role of financial instabilities in influencing the distribution of future GDP growth across countries. By analysing the relationship between financial conditions and economic growth, I aim to shed light on how variations in financial stability can have a profound impact on a nation's economic performance. This investigation will offer crucial insights into the potential risks and opportunities associated with financial conditions in different economies.

Furthermore, the examination of these indexes will enable me to explore the existence of possible co-movements in financial conditions across countries. Identifying patterns of synchronized financial movements among nations can have significant implications for global financial markets and economic interdependence. This analysis will help uncover potential contagion effects, spillover mechanisms, and the presence of shared vulnerabilities that may amplify the impact of financial shocks on an international scale.

1. US Financial Conditions Indexes Construction

1.1 Data

In the quest to construct an index that can effectively replicate the US NFCI, I embark on a meticulous process of selecting a set of financial and macroeconomic metrics[4] capable of signalling potential financial frictions. The foundation for selecting these "starting variables" lies in their theoretical significance, as they offer valuable insights into a country's financial stability. For a more comprehensive understanding of these variables and their theoretical relevance in highlighting financial vulnerabilities, additional insights are provided in Appendix 1. While theoretical relevance is crucial, practical considerations also play a pivotal role in this endeavour. Ensuring replicability in the construction of the Financial Conditions Index (FCI) is of paramount importance. To achieve this, the chosen variables are not only theoretically significant but are also commonly available for most countries, regardless of their level of development. This approach facilitates a relatively straightforward replication of the index across different countries and regions. The initial set of variables considered for inclusion in the index encompasses a range of financial and macroeconomic indicators that provide critical information on a country's financial health and potential risks. These variables serve as the building blocks for the construction of the FCI and can be combined into various families of variables[5], such as:

1. Amount of Credit Outstanding
2. Credit Risk Premium
3. Interbanking System Interest Rates
4. Banking System Risk Provisions
5. Public Debt
6. Exchange Rates
7. Equity Volatility & Equity Risk Premium
8. Government Bond Yield Maturity Spread

[4] All data is gathered from the Refinitiv Eikon Datastream platform, which collects data from the major public institutions.
[5] Discussed in detail in Appendix 1

All the series are referred to US and refer to the period going from 1993.Q1 to 2022.Q4, in quarterly frequencies and at constant prices. Moreover, to assure that the indexes computations are not influenced by the variables' measurement units and relative magnitude of individual series, all the variables have been normalized. Also, I do not compute data differences to ensure stationarity since the empirical framework employed does not require data stationarity. Finally, as the data are selected, in the next section I expose the methodology adopted to summarize this set of variables into one specific index. Ultimately, and of utmost significance in the calculation process, I inverted the variables signs that tend to exhibit higher values when financial conditions are robust. This inversion was crucial in establishing a distinct ranking, where elevated variable values are effectively linked to tight financial conditions, and vice versa.

1.2 Methodology

I use the Principal Component Analysis (PCA) as empirical approach to analyse the set of financial metrics stated above. This analysis allows to identify patterns in the data and express it in a way that highlights similarities and differences. This process helps to compress the data without losing relevant information. By doing so, I can reduce the number of variables in the dataset and focus on the primary drivers of the data.

Algebraically to obtain the principal components, I compute the eigenvalue decomposition of the observed variance matrix. Each component obtained is an optimal linear combination of the observed variables, with the first component accounting for the maximal amount of variance in the observed variables. Subsequent components maximize variance among unit-length linear combinations that are orthogonal to the previous components. The loadings of each variable in the linear combinations provide an interpretation for the principal components, while the principal components themselves can be used as summary variables in subsequent analysis. This methodology involves no estimation and thus no error term, which is also the reason because I do not employ more recent estimation methodologies based as an example the factor augmented vector autoregressive models with time-varying coefficients and stochastic volatility developed by Koop and Korobilis (2014).

Pragmatically, the Principal Component Analysis returns the weights of each variable in each component, multiplying these weights to the associated variables in any period I can construct the time series of each component. These components are then combined into a Financial Conditions Index, which I use to analyse the intertemporal evolution of financial conditions during the selected time span. I use a threshold for the share of total variance explained to decide which components to use in the construction of the financial conditions index. The combination of multiple components is quite straightforward, the constructed index is the weighted average of the components included in it, where the weights are represented by the portion of total variance explained by each component.

1.3 Practical Indexes Computation

Using all the 20 initial variables listed in Appendix 1, I construct several indexes for the US by: computing all the possible combinations of variables to be used, then I construct for each of the selection of variables several financial conditions indexes using PCA with different variance thresholds. To be precise, to assure the computability of these indexes, I computed all the possible combinations of variable selection and using as variance thresholds only the 70% and 90% ones. The computation has been not straightforward and a total of 2,069,222[6] FCIs have been estimated for the US.

2. US Financial Conditions Index Validation

2.1 Methodology

After estimating all the indexes, the next step involves selecting the most appropriate index to be used in subsequent analyses. To achieve this, a straightforward methodology is employed: I choose the index that best mimics the official NFCI developed by the FED, maximizing its correlation with the constructed Financial Conditions Index (FCI). To ensure an unbiased measure unaffected by the sample size and to avoid potential random effects due to a high number of indexes constructed over a limited number of observations, a careful approach is taken. The estimation of the indexes is not based on the entire time series length, but rather on the first 80% of the series (96 observations), referred to as the training set. The variable weights are estimated using this training set, and then the indexes are computed over the entire time series of the variables. Consequently, two types of estimates are obtained: the in-sample predictions based on the training set (first 96 observations) and the out-of-sample predictions based on the testing set (last 24 observations).

By adopting this methodology, the construction of the indexes is more safeguarded against "data mining" tendencies, ensuring that the desired outcome of mimicking the official index is

[6] An unspecified quantity of these, however, turns out to be duplicated. In any of the sub-selections of variables, it's plausible for two indexes that meet the 70% and 90% variance thresholds in PCA to align. Consequently, the precise count of distinct FCIs constructed remains unidentifiable.

not merely coincidental. To determine the index that exhibits the highest resemblance to the official NFCI, correlations are computed in three distinct ways: using the overall time series, the in-sample estimates, and the out-of-sample estimates. To strike a balance between different correlation measures and to emphasize the out-of-sample predictive power of the index, I opt to use the average of the in-sample and out-of-sample correlations as the final decision variable. This choice is motivated by the necessity to assign varying weights to the correlation measures and to underscore the importance of the index's predictive performance in the out-of-sample context. Additionally, to ensure the consistency of results and avoid inexplicable differences in performance between in-sample and out-of-sample correlations, I apply a filtering process. Indexes that exhibit differences in correlation of more than 0.10 between in-sample and out-of-sample estimates are excluded from the selection process.

By adhering to this comprehensive methodology, I aim to arrive at a robust and reliable index that accurately reflects the financial conditions of different countries while minimizing any potential biases or chance correlations. This rigorous index selection process contributes to the credibility and soundness of the subsequent analyses, providing valuable insights into the interplay between financial conditions and economic performance across diverse economies.

2.2 Results

The results of the different correlation measures of the best 10 constructed indexes over the total constructed indexes and the official NFCI for the US are shown in Table 1.

Table 1. Best constructed Financial Conditions Indexes Correlations to the official NFCI
The table shows the characteristics and the results in terms of correlations of the best constructed indexes. The index highlighted in grey indicates the index selected as the most accurate in mimicking the official US NFCI, and it is the one utilized for further analyses.
Country: US. Timespan: 1993.Q1 - 2022.Q4. Frequency: Quarterly.

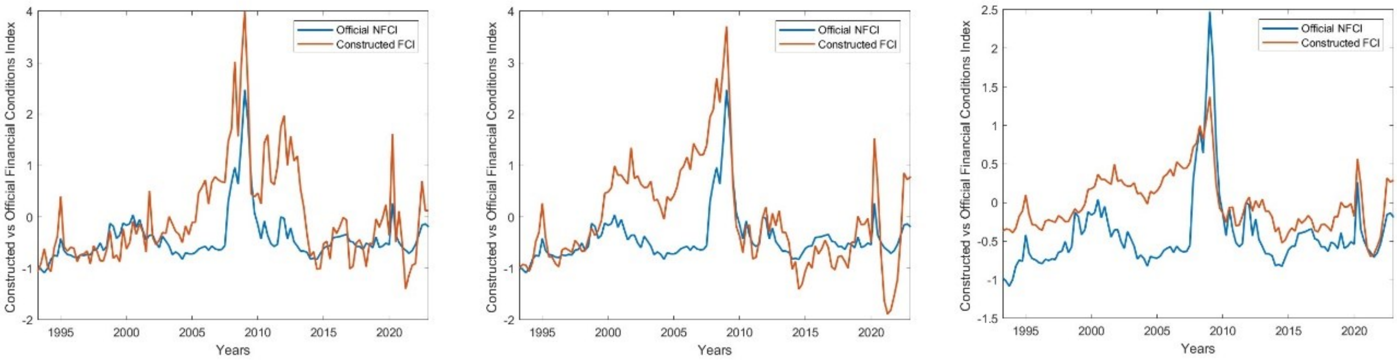
Number of variables included	PCA Variance threshold	In-Sample Correlation	Out-of-Sample Correlation	Total Correlation	In and out of sample correlation average	Filter Result[7]
7	90%	0.6679	0.9038	0.6722	0.7859	X
7	90%	0.6679	0.9038	0.6722	0.7859	X
7	**90%**	**0.7578**	**0.8095**	**0.7535**	**0.7836**	**V**
8	90%	0.7174	0.8485	0.7022	0.7830	X
8	90%	0.7174	0.8485	0.7022	0.7830	X
9	90%	0.7477	0.8168	0.7435	0.7822	V
8	90%	0.7449	0.8185	0.7408	0.7817	V
8	90%	0.7449	0.8185	0.7408	0.7817	V
9	70%	0.7207	0.8394	0.7054	0.7800	X
7	90%	0.7207	0.8394	0.7054	0.7800	X
Best 1,000 Average		0.5640	0.7748	0.5540	0.6694	
Best 10,000 Average		0.5157	0.7550	0.5070	0.6354	

The outcomes are largely favourable. Over 75% of the created indexes exhibit a total correlation with the official index different from zero at a 5% significance level. No single index has been constructed with a total correlation statistically indistinguishable from 1 when compared to the official index. This highlights the challenge of precisely replicating all patterns within the official index using solely publicly available data. Nonetheless, the most effective indexes, which maintain a robust correlation exceeding 0.70, provide me with the confidence to assert the capability of these indexes to capture key financial trends in the US economy.

[7] In this column, I write “V” if the absolute value of the difference between in-sample and ouf-of-sample correlations is smaller than 0.10, otherwise I put ”X”. This column filters to have only indexes in which the in-sample and ouf-of-sample correlations does not differ too much.

The indexes display a general interrelationship, displaying only minor disparities among them. To illustrate this, Figure 2 illustrates a comparison between the three best performing indexes constructed in terms of overall correlation with the official NFCI.

Figure 2. Best 3 Performing Constructed Indexes in mimicking the official US NFCI
The panels show the best 3 performing indexes in terms of in and out-of-sample correlation averages with the official US NFCI.
Country: US. Timespan: 1993.Q1 - 2022.Q4. Frequency: Quarterly.



These three indexes are very similar to each other with some minor differences in the pattern, this is the result of the similarities in the variables selection and overall, in the final weights of the included variables in the indexes. Understanding the consistency of the results for all the best constructed indexes, I decide to select the one that maximize the average of in and out-of-sample correlation with the official NFCI. This index is plotted again in Figure 3 and the characteristics of it are included in Table 2.

Figure 3. Selected synthetic US Financial Conditions Index
The panel shows the selected index plotted along with the official US NFCI.
Country: US. Timespan: 1993.Q1 - 2022.Q4. Frequency: Quarterly.

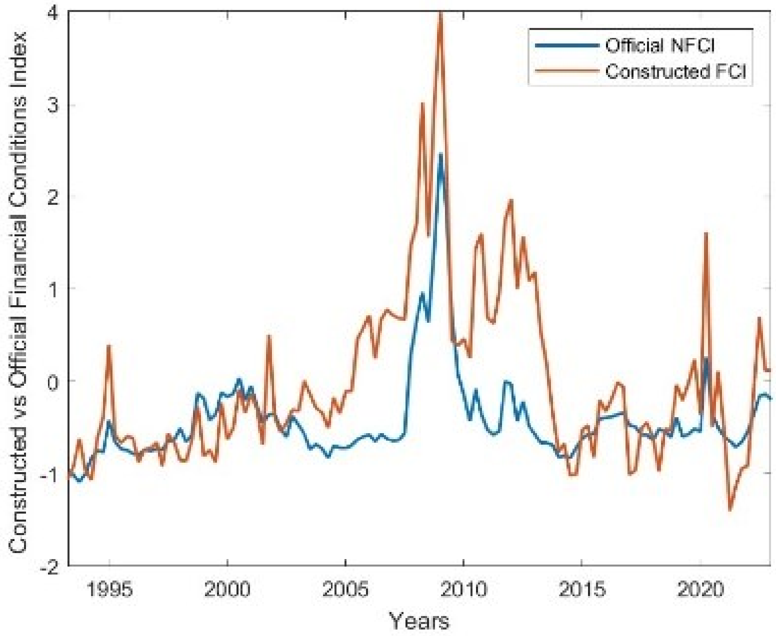


Table 2. Best constructed Financial Conditions Index Variables and Weights
The table shows the variables included and the weights of these in constructing the selected Financial Conditions Index.
Country: US. Timespan: 1993.Q1 - 2022.Q4. Frequency: Quarterly.

Variables	Variables Total Weights
Loans and Leases in Bank Credit Outstanding	32.30%
Equity Risk Premium	31.72%
Average Credit Risk Premium in Banking System (Prime Rate – Government Bond Rate (10 Years Maturity))	27.02%
Commercial and Industrial Loans Outstanding	19.24%
Government Bond Yield Maturity Spread (1 Year – 3 Months)	10.42%
Total Provisions for loans losses	-15.03%
Gross Public Debt-GDP ratio	-5.66%

2.3 Some considerations

The results obtained in terms of correlations remain consistent when using alternative methodologies, such as encoding algorithms, simple averages, and Kalman filter. However, the Principal Component Analysis (PCA) stands out as the most effective tool for accurately summarizing diverse patterns and capturing the overall financial conditions for the US in a single time series. As a matter of fact, PCA is the dominant methodology in major central banks, as the Fed, due to its ability to efficiently capture and decompose primary and secondary data patterns with minimal information loss. It estimates variables' weights that effectively represent total weights in both primary and secondary patterns through variance decomposition. PCA stands out for its interpretability and generality, especially when compared to recursive machine learning techniques that aim to maximize the correlation between the synthetic indices and the official one. While these techniques focus solely on fitting data closely, PCA excels in highlighting the relative importance of selected variables in explaining patterns that represent overall financial stability in economies.

Furthermore, I have observed that, even when altering the composition of the training and testing sets, the results remain robust with minimal variations. Additionally, among the best computed indexes, there are generally no substantial differences in the selection of variables to be included, and only slight differences in the weights assigned to these variables do not significantly impact the overall findings. This robustness underscores the reliability and validity of the selected indexes, reinforcing their suitability for further analyses and discussions on financial stability and its implications for economic growth.

3. Financial Conditions Indexes for other economies

Following the meticulous crafting of the US FCI, the next step involves the replication of this index across a diverse set of nations: the Euro Zone, Argentina, Brazil, and India.

This step represents a significant contribution to the field as, to the best of my knowledge, there has been no prior adoption of a methodology capable of creating a consistent index for assessing the financial conditions of economies across various countries and regions. The previous steps were essential to pave the way for the next one. In fact, due to data unavailability, directly replicating the US official financial conditions index for other economies becomes impossible. Hence, the construction of a replicable synthetic index, discussed in the preceding sections, is necessary.

The selection of the nations to be analysed emerges from the intent to not only underscore the impact of financial conditions over countries economic activity within developed economies, typified by the US and Euro Zone, but also to cast a spotlight on the impact within developing economies, analysing the latter three. Furthermore, the rationale for analysing these three developing economies is rooted in their distinct historical financial situations, with Argentina, notably, known for its historically financial turbulences. The ensuing sections bifurcate this endeavour into a dual discourse: firstly, the construction and presentation of the Financial Conditions Index for these nations; subsequently, a comprehensive exploration delves into the interplay of these indices, unearthing potential contagion effects that traverse the boundaries of these disparate economies.

3.1 Indexes Construction

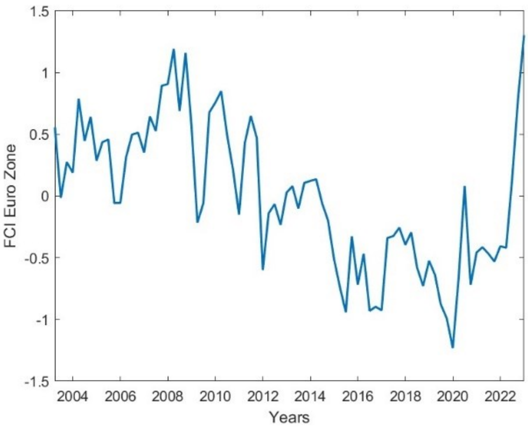
After successfully estimating a suitable index for the US, assuming that the official NFCI reliably captures the dynamics of financial conditions in the country, I can now replicate this index to other countries. The replication process is straightforward; it involves applying the weights calculated for the US in the construction of the official NFCI mimicking index to the selected data from these other countries. However, it is essential to acknowledge a potential limitation in this methodology. The variables that hold significant relevance for the US might not carry the same level of importance for other countries. Consequently, there could be variations in the effectiveness of the replicated index in capturing the financial conditions dynamics of different countries. Despite this limitation, this approach still offers a valuable proxy for assessing the financial conditions of these countries and provides an appropriate counterfactual for comparison with the US case. Indeed, the chosen variables and their corresponding weights have demonstrated, in their analysis of US data patterns, a remarkable capacity to nearly fully account for the financial conditions of the country, with significantly less data[8] and computational effort. Consequently, these variables and weights emerge as the most compelling option for computing similar indexes for other countries.

Figure 4 shows the constructed FCIs for all the analysed countries and the relation between real GDP growth and the Financial Conditions of each country at different time (quarters) lags.

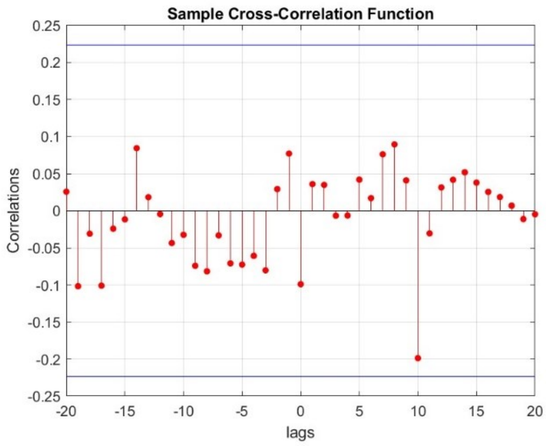
[8] The synthetic index requires significantly less data, approximately 93.33% less, compared to the official index, given that it comprises only 7 metrics in contrast to the official index's 105.

Figure 4. Constructed FCIs and their correlation with economic growth
The panels show, on the left side, the resulting constructed Financial Conditions Index for each of the countries analysed (Euro Zone, Argentina, Brazil, India). On the right side, the cross correlogram between the FCIs and real GDP growth of each country is shown.
Country: Euro Zone. Timespan: 2003.Q1 - 2022.Q4. Frequency: Quarterly.
Country: Argentina. Timespan: 2004.Q2 - 2022.Q4. Frequency: Quarterly.
Country: Brazil. Timespan: 2004.Q1 - 2022.Q4. Frequency: Quarterly.
Country: India. Timespan: 2002.Q1 - 2022.Q4. Frequency: Quarterly.

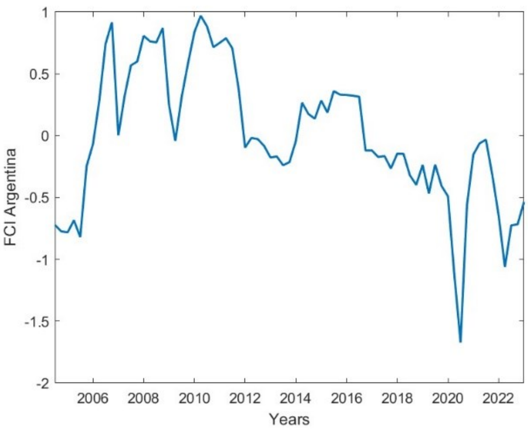
1. Euro Zone: Constructed FCI



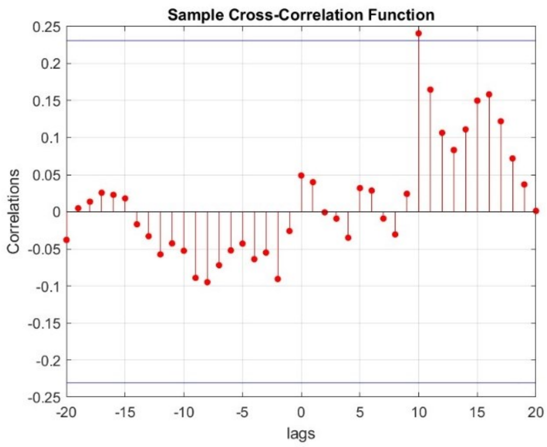
2. Euro Zone: Cross-correlogram between GDP growth and constructed FCI



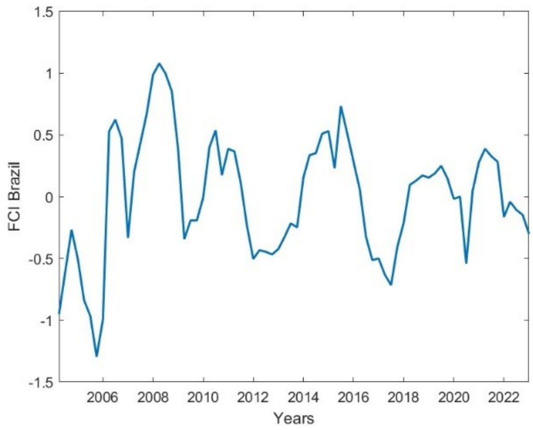
3. Argentina: Constructed FCI



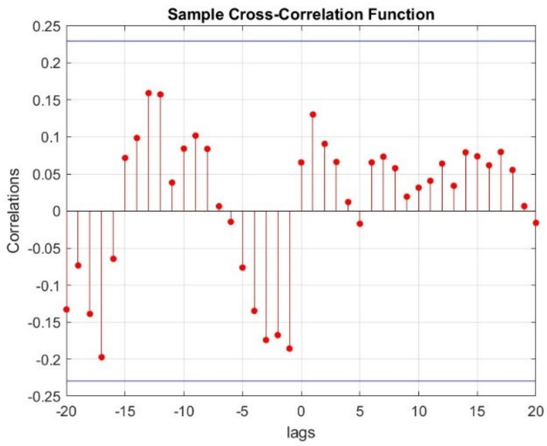
4. Argentina: Cross-correlogram between GDP growth and constructed FCI



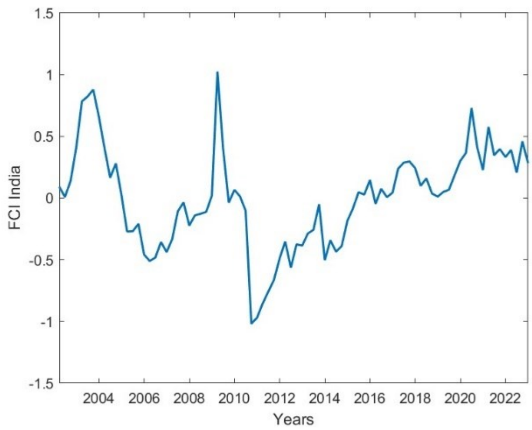
5. Brazil: Constructed FCI



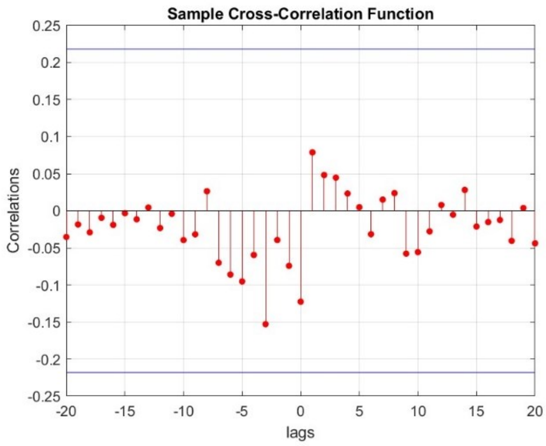
6. Brazil: Cross-correlogram between GDP growth and constructed FCI



7. India: Constructed FCI



8. India: Cross-correlogram between GDP growth and constructed FCI

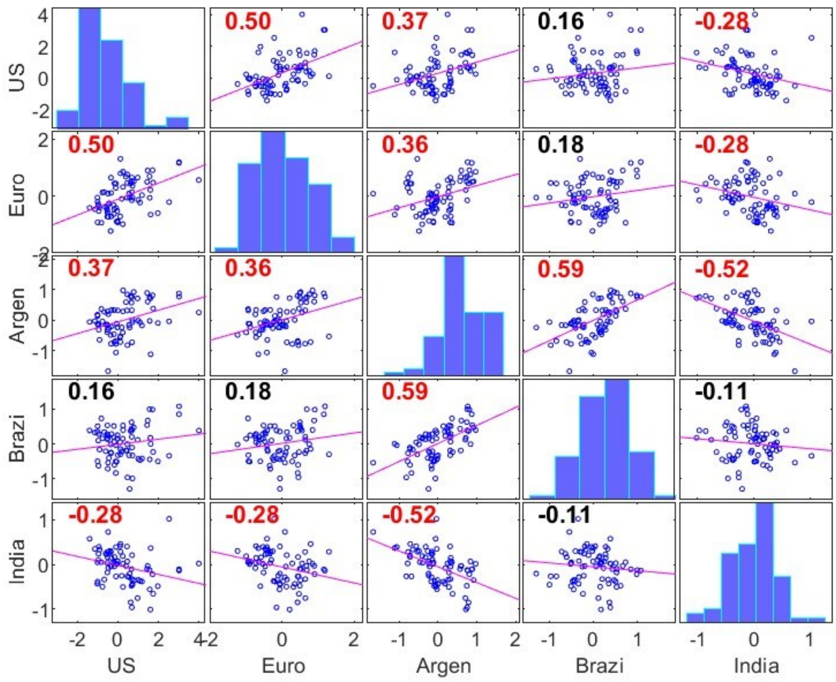


The panels, while exhibiting variations, reveal an overarching shared pattern and notable resemblances, particularly during periods of global tensions such as the 2007-2009 financial crisis stemming from the US mortgage market collapse, as well as the current financial turbulence triggered by the aftermath of the pandemic and the Russian-Ukrainian conflict. In summation, the indexes appear to correctly summarize the financial landscapes of the studied economies. In the next section, I explore the links that intertwine between the financial conditions of these economies to investigate potential contagion effects, spillover mechanisms, and the presence of shared vulnerabilities that may amplify the impact of financial shocks on an international or even global scale.

3.2 Indexes Analysis

The formulated indices appear to serve as a promising visual representation for summarizing the financial conditions across the analysed countries. My focus now shifts towards exploring variations in financial stability among these economies. Nevertheless, a direct comparison based on the current indices is unfeasible due to the normalization process needed for the computation of the indexes, which renders the distribution of indices identical[9]. For this reason, I proceed to investigate the relationship between the indexes in terms of correlation between them to investigate possible shared vulnerabilities or contagion effects across countries in terms of financial stability. To do so, I present in Figure 5 the correlations across all the pairs of indexes of the countries.

Figure 5. Correlation between countries financial conditions
The panel shows the correlation matrix of all the countries analysed. All the correlations statistically significant from zero at 5% significance level are in red.
Country: US, Euro Zone, Argentina, Brazil, India. Timespan: 2004.Q2 - 2022.Q4. Frequency: Quarterly.



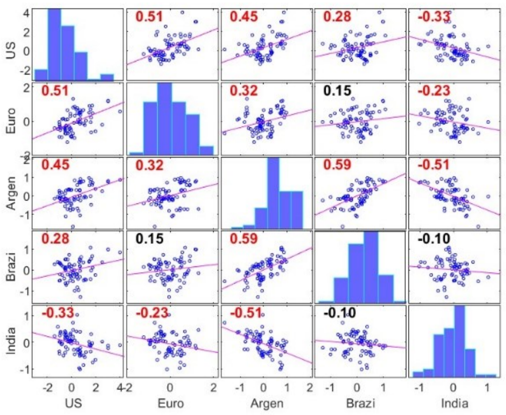
[9] A standardized normal distribution.

The findings present an intriguing scenario, characterized by a general tendency of countries to move together, except for India which stands as an exception. Of notable significance are the correlations observed between the two developed economies under scrutiny (0.50), underscoring a strong linkage between their financial markets. Equally compelling are the results pertaining to the South American pair, Argentina-Brazil, revealing a pronounced interrelationship between them (0.60). However, a divergent pattern emerges for India in contrast to the other countries, indicating a general independence or even a negative relationship. This divergence could be attributed to India's geographical and cultural remoteness from the other nations, coupled with its less-integrated status in international finance. Despite these variations, the outcomes collectively highlight a significant level of interplay among the financial conditions of these nations.

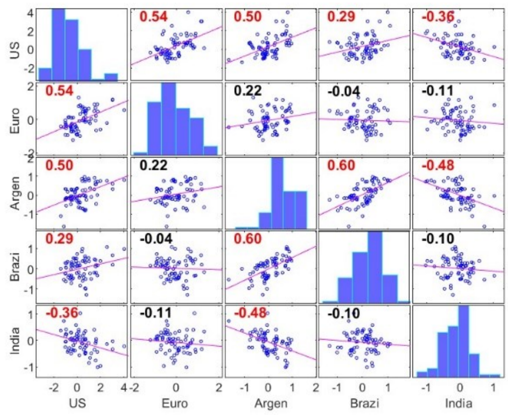
It's important to note that the current analysis focuses solely on the contemporaneous relationships between these countries. It's plausible that the propagation of financial frictions might not be immediate and could take time to diffuse. To further analyse this aspect, Figure 6 displays the same correlation matrix with a simultaneous assumption. Panels 1 and 2 depict the correlation of developed economies' financial conditions with those of the developing economies one quarter and one year ahead. This exploration seeks to unveil potential spill-over effects from developed economies to developing ones. Conversely, panels 3 and 4 reverse the perspective to investigate the inverse phenomenon.

Figure 6. Correlation between countries financial conditions with one and four time lags
The panels show the correlation matrix for the examined countries, revealing different time lags within clusters: developed economies (US, Euro Zone) and developing economies (Argentina, Brazil, and India). All the correlations statistically significant from zero at 5% significance level are in red. Country: US, Euro Zone, Argentina, Brazil, India. Timespan: 2004.Q2 - 2022.Q4. Frequency: Quarterly.

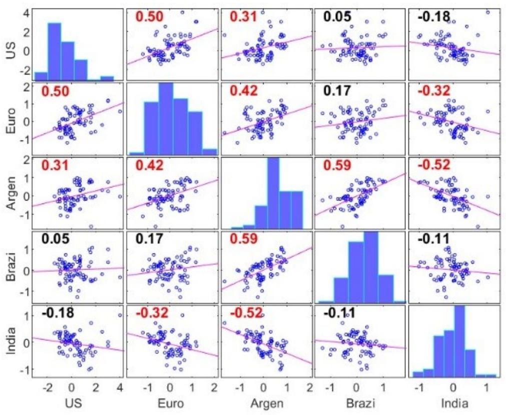
1. Developed economies one quarter ahead (t+1) vs. Developing economies (t)



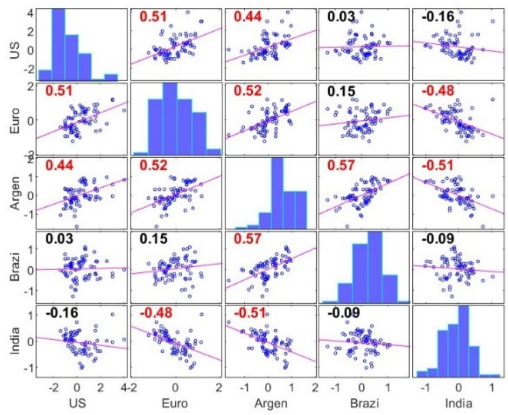
2. Developed economies one year ahead (t+4) vs. Developing economies (t)



3. Developed economies (t) vs. Developing economies one quarter ahead (t+1)



4. Developed economies (t) vs. Developing economies one year ahead (t+4)



These outcomes in this instance do not yield additional evidence, the previously noted cross-country relationships persist. The plots once again underscore the interlinkages among countries in terms of financial conditions, except for the Indian case. These patterns hint at a significant level of financial integration between these nations.

This analysis concludes this chapter, which led to the construction of robust indicators for financial conditions for each of the countries analysed. The following chapter delves into the subsequent phase, involving the evaluation of how financial conditions can potentially impact the real GDP growth of these nations, shaping the growth trajectories of both developed and developing economies over time.

IV. Econometric Estimation Model & Main Findings

Once the Financial Conditions Index has been computed, I proceed following closely Adrian et al. (2019) to estimate GDP complete distribution over time in order to investigate the financial conditions role in affecting economies real growth and risk exposures to this growth. In this section, I give a detailed exposition of the utilized methodology.

1. Model Estimation

1.1 Conditional Quantiles Estimation

Starting with the real econometric model, I can formerly address the relationship between financial conditions and GDP growth, utilizing quantile regression (following the original authors notations), estimated with quantiles τ from 5% to 95% (with a 5% step), using the formula:

$$y_{t+h}(\tau|x_t) = \beta_\tau x_t + \varepsilon_t$$

where y_{t+h} is the annualized growth rate of real GDP between t and t + h, x_t represents a vector of conditioning variables, including GDP growth, a constant term and the constructed FCI. This regression is repeated with both $h = 1$ and $h = 4$, to investigate the current GDP growth dependence to the values of the series itself and more importantly to financial conditions a year (4 quarters) and one quarter in the past.

The estimation of the β_τ differs form a classic Ordinary Least Square regression because it minimizes the sum of absolute (and not squared) errors, assigning differential weights on the errors depending on whether it is above or below the quantile. Then, using the estimated coefficient $\hat{\beta}_\tau$ provides the quantile predicted value of y_{t+h}, given x_t.

$$\widehat{Q}_{y_{(t+h|x_t)}}(\tau\,|xt) = x_t\hat{\beta}_\tau$$

This quantile regression gives an approximate estimate of the quantile function of the series, which is the inverse cumulative distribution function.

1.2 GDP Growth Probability Distribution Functions Estimation

However, given the difficulties in mapping these estimates in probability distribution functions, I proceed by smoothing the quantile regression estimates using a skewed t-distribution developed by Azzalini and Capitanio (2003), to get a complete probability density function of the real GDP growth. The proposed skewed t-student distribution is defined as in the original paper by the Pdf:

$$f(y;\mu,\sigma,\alpha,v) = \frac{2}{\sigma} t\left(\frac{y-\mu}{\sigma};v\right) T\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{v+1}{v+\frac{y-\mu}{\sigma}}};v+1\right)$$

Where t(·) and T(·) represent t-Student PDF and CDF functions, respectively, which have four parameters determining the series' location, scale, fatness, and shape of the distribution (μ,σ,α,v) in each period. The location parameter μ represents the central value of the distribution, so in this case represents for each period the average real GDP growth rate. The scale parameter σ represents the dispersion around the central value and reflects the degree of uncertainty in the economy regarding growth. The fatness, instead, measured by the distributions degree of freedom determines the relative thickness of the tails of the distributions. This measure is the main variable in determining the likelihood of extreme real GDP growth relative to the central value. Finally, the shape parameter α represents the real difference from a standard t-Student distribution determining the skewness of the CDF on the PDF, impacting the likelihood of the real GDP growth to be above or below the central value in any point in time.

This thesis uses a regression approach in the cross-section to estimate these four parameters $\{\mu_t,\sigma_t,\alpha_t,v_t\}$ of the distribution. This is done by minimizing the squared distance between the estimated quantile function and the quantile function of the skewed t-distribution for the 5, 25, 75, and 95 percent quantiles.

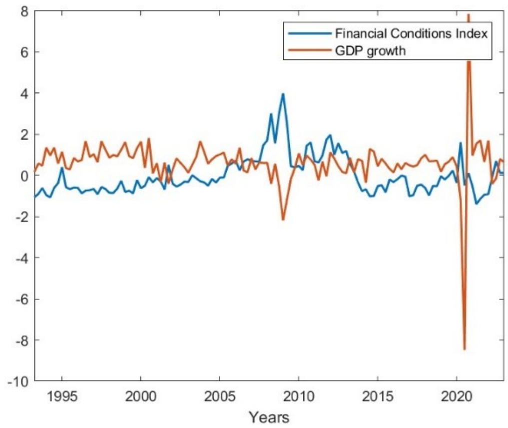
$$\{\hat{\mu}_{t+h},\hat{\sigma}_{t+h},\hat{\alpha}_{t+h},\hat{v}_{t+h}\} = argmin_{\mu,\sigma,\alpha.v}\sum_{\tau}\left(\widehat{Q}_{y_{t+h}|x_t}(\tau|x_t) - F^{-1}(\tau;\mu,\sigma,\alpha,v)\right)^2$$

1.3 Model Inputs

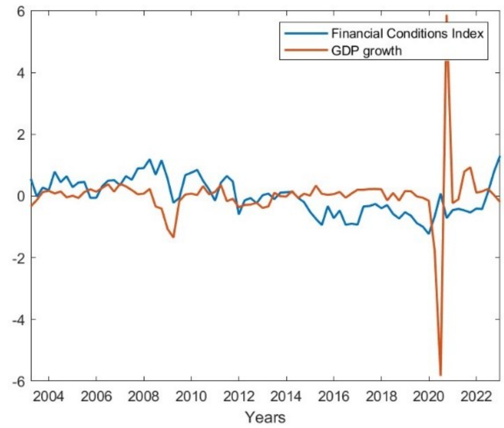
In this model, the inputs consist of two key variables for each of the countries under analysis: the actual real GDP growth and the corresponding Financial Conditions Index (FCI), which has been constructed using the data and methodology thoroughly exposed in the previous chapter. Specifically, the chosen metric for GDP growth is the time series of GDP Growth at Constant Prices (2015=1). Figure 7 illustrates the time series of real GDP growth and the constructed FCI for each country analyzed, while Table 3 provides summary statistics of these metrics.

Figure 7. Real GDP Growth and Financial Conditions
The panels show the time series of real GDP growth (normalized to have an appropriate scaling) and of constructed Financial Conditions Index for each of the countries analysed (Euro Zone, Argentina, Brazil, India).
Country: US. Timespan: 1993.Q1 - 2022.Q4. Frequency: Quarterly.
Country: Euro Zone. Timespan: 2003.Q1 - 2022.Q4. Frequency: Quarterly.
Country: Argentina. Timespan: 2004.Q2 - 2022.Q4. Frequency: Quarterly.
Country: Brazil. Timespan: 2004.Q1 - 2022.Q4. Frequency: Quarterly.
Country: India. Timespan: 2002.Q1 - 2022.Q4. Frequency: Quarterly.

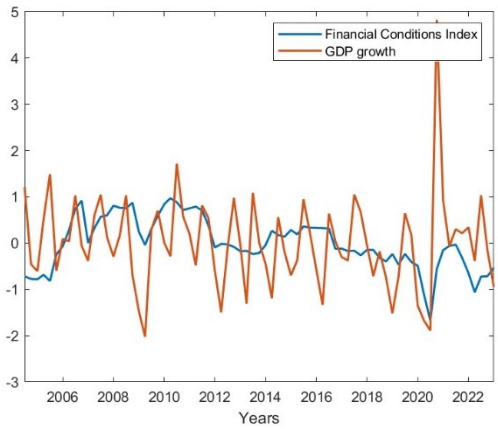
1. US



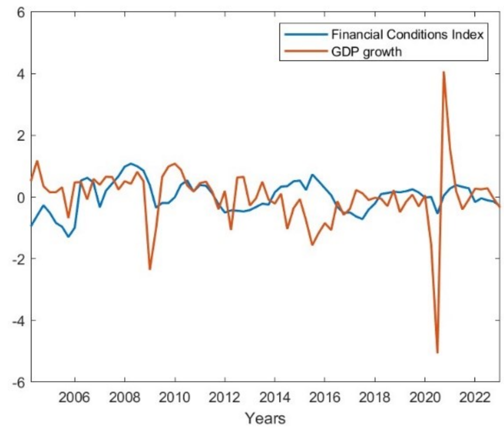
2. Euro Zone



3. Argentina



4. Brazil



5. India

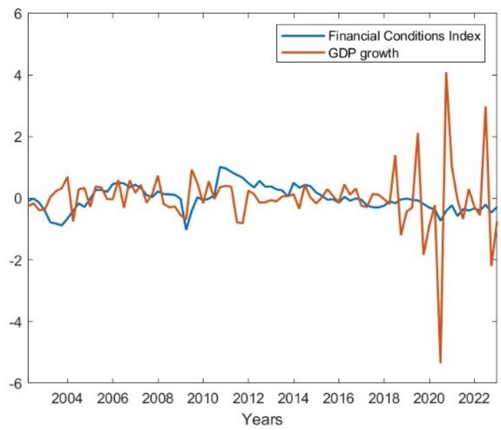


Table 3. GDP growth and FCI summary statistics
The table shows the summary statistics of real GDP growth and FCI of each of the countries analysed.

Country	Variables	Observations	Mean	Standard Deviation	5^{th} Percentile	95^{th} Percentile
US	GDP growth	120	0.61	1.22	-0.41	1.66
	FCI	120	0.00	1.00	-1.00	1.71
Euro Zone	GDP growth	80	0.32	2.01	-0.56	1.09
	FCI	80	0.00	1.00	-0.93	0.89
Argentina	GDP growth	75	0.60	2.97	-3.90	4.10
	FCI	75	0.00	1.00	-0.79	0.85
Brazil	GDP growth	76	0.56	1.81	-1.73	2.40
	FCI	76	0.00	1.00	-0.87	0.76
India	GDP growth	84	1.61	3.59	-1.59	5.20
	FCI	84	0.00	1.00	-0.72	0.65

From these Figures, the linkage between financial conditions and economic growth becomes evident. In general, periods of economic downturns are anticipated by pronounced spikes in the FCIs, which serve as indicators of notably constrained financial conditions. Furthermore, the discrepancies in real GDP growth statistics underscore variations in economic stability among different countries. Argentina, for instance, exhibits clear evidence of economic growth instability, as indicated by a notably elevated 95^{th} - 5^{th} percentile range of GDP growth compared to other nations[10], and the highest standard deviation.

These observations fuel the intrigue surrounding this topic and underscore the necessity for a more in-depth investigation into how financial conditions impact the real economy and how this relationship changes in different economies.

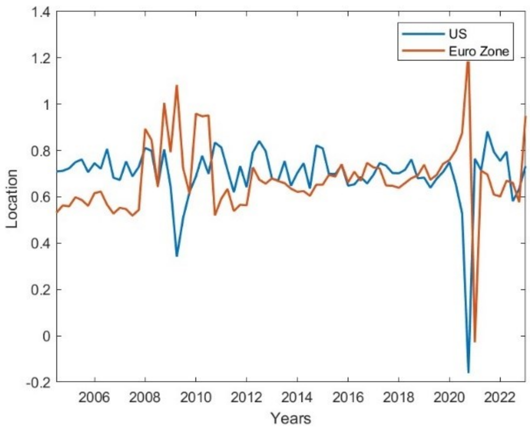
[10] 95^{th} - 5^{th} percentile range of GDP growth: 8.00 Argentina vs 3.70 average other nations.

1.4 Estimation Results

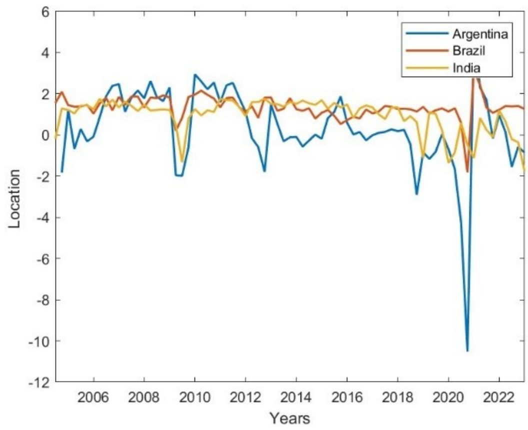
After providing a comprehensive description of the econometric model along with its key input variables, I can now proceed to display its estimation results. To begin, the estimates through time of the four parameters of the distributions of all the analyzed countries, divided for visualization purposes in developed economies (US, Euro Zone) and developing economies (Argentina, Brazil, India) are shown in Figure 8, referring to the model with a lag of one quarter in the Financial Conditions Index and GDP growth as regressors[11].

Figure 8. Moments estimates using regressors with one quarter lag
The panels show the real GDP growth estimated moments $\{\hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{v}_{t+h}\}$ smoothing the quantile functions over the skewed t-distribution, for estimates one quarter ahead (h = 1). The countries are clustered, for visualization purposes, in: Developed Economies (US, Euro Zone) and Developing Economies (Argentina, Brazil, India).

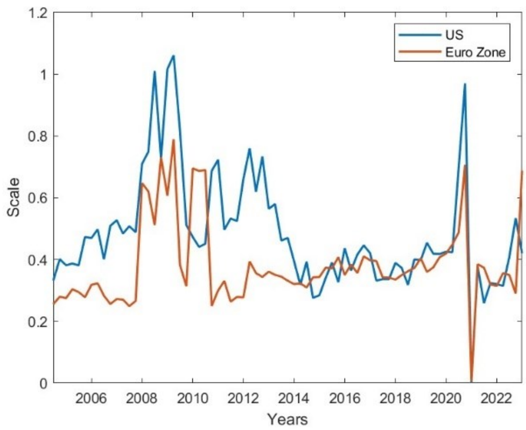
1. Location: Developed Economies



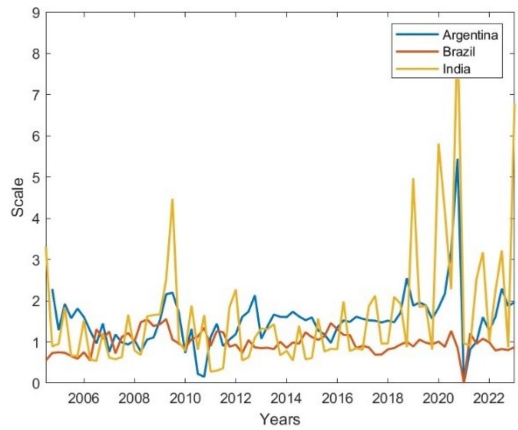
2. Location: Developing Economies



3. Scale:Developed Economies

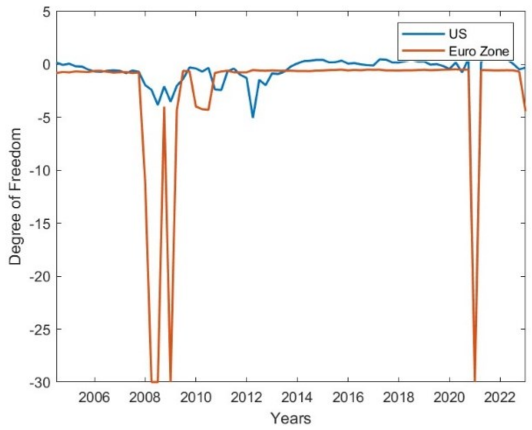


4. Scale: Developing Economies

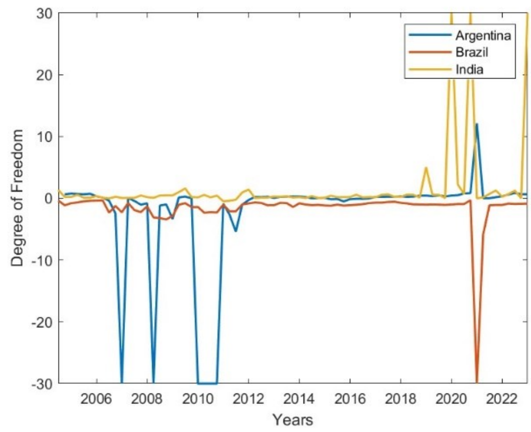


[11] Starting now, in this thesis, every figure pertains to the model with a one-quarter lag in the conditioning variable(s). The equivalent figures resulting from the one-year lag models can be found in Appendix 2.

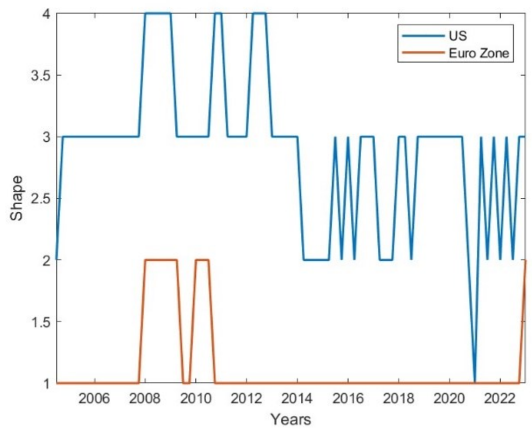
5. Degree of Freedom: Developed Economies



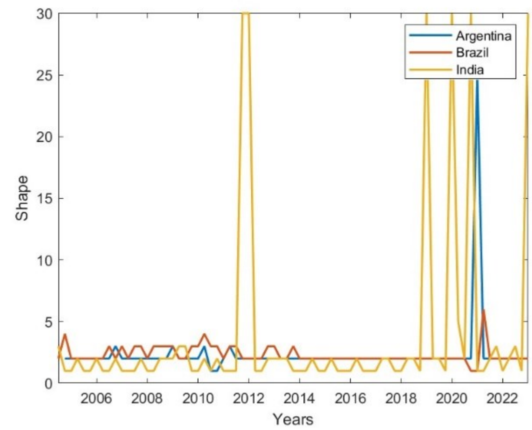
6. Degree of Freedom: Developing Economies



7. Shape: Developed Economies



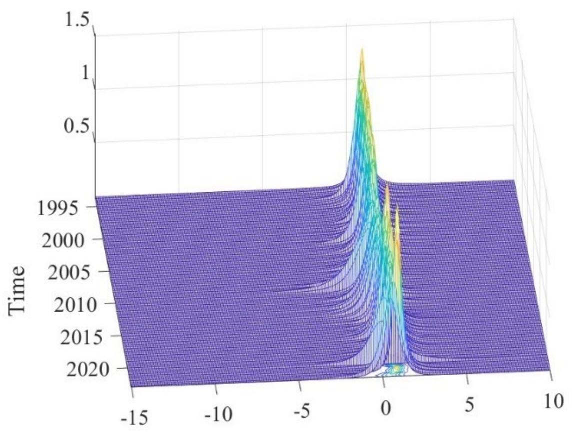
8. Shape: Developing Economies



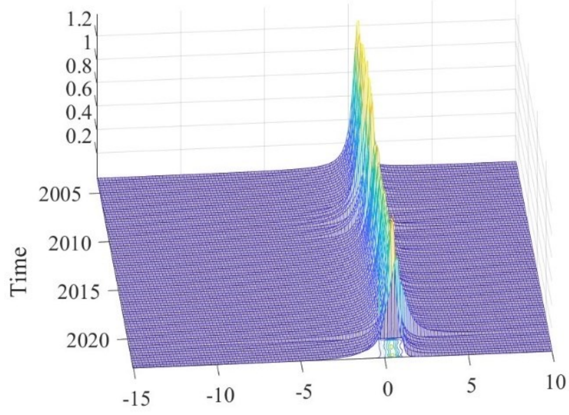
While these plots may not immediately exhibit clear interpretive outcomes, it's crucial to recognize several important aspects. To start, I want to emphasize that across all countries, the various moments represent temporal shifts, highlighting that changes in economic growth realizations over time are generally accompanied by shifts in its complete distribution. Additionally, significant disparities exist in these moments among countries, particularly between developed and developing nations. These disparities become distinctly evident in the estimates of the location parameter, which display notably different scaling measures between the two clusters of countries. Even more significant are the distinctions observed in the remaining three moments, with the scale parameter being the most crucial. This parameter underscores how, for developing economies, the extent of dispersion around the median of real GDP growth serves as a pivotal factor influencing growth realizations over time. The computation of these moments at any specific time permits the plotting of the complete distributions of real GDP growth estimates for each country, which stands as the central goal of this model. These plots enhance the interpretation of the results obtained from estimating these moments and can be found in Figure 9.

Figure 9. GDP growth density distribution, one quarter lag model
The panels show the one quarter ahead (h = 1) estimates of real GDP growth full distributions for each of the analyzed country. Estimated using quantile regressions with both real GDP growth and the Financial Conditions Index as independent variables.

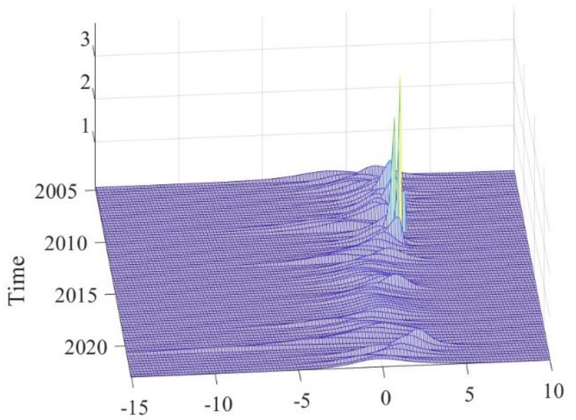
1. US: one quarter lag model



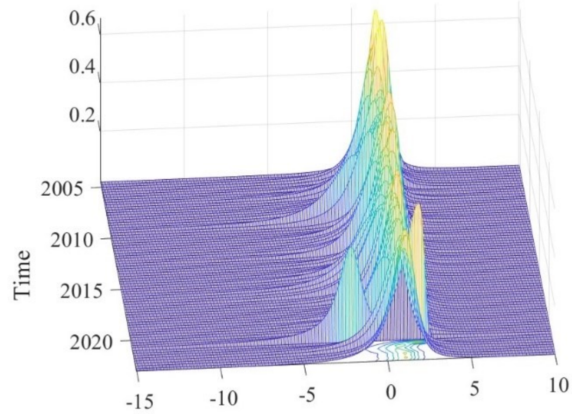
2. Euro Zone: one quarter lag model



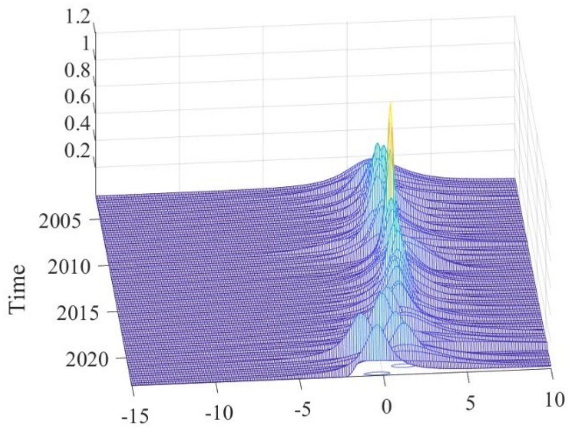
3. Argentina: one quarter lag model



4. Brazil: one quarter lag model



5. India: one quarter lag model



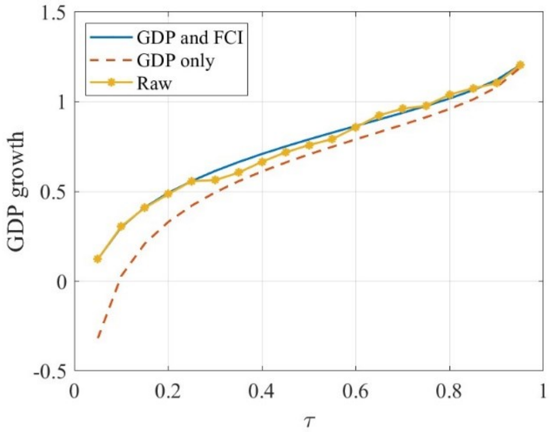
The figures presented above clearly illustrate how the distribution of GDP growth for all countries evolves over time. This provides a more accessible and intuitive representation compared to Figure 8. These previous figures underscore the significance of economic and financial conditions when forecasting moments of GDP growth, especially the scale and fatness parameters. It is noteworthy that periods of economic expansion tend to be associated to perfectly Gaussian distributions, whereas recessions are associated typically with distributions with an increased scale and fatness, and with left skewness. This pattern is evident in both the Global Financial Crisis of 2007-2009 and in the more recent recession triggered by the Covid-19 pandemic in 2020. These findings emphasize the pivotal role that financial conditions play in estimating real GDP growth, impacting not only the first moments but also the higher moments of the distribution.

Moreover, these results vary significantly across different countries. In fact, they can be categorized into three groups. First, the United States and the Euro Zone exhibit the most stable distributions over time, demonstrating consistent GDP growth distributions with only minor fluctuations. Second, Brazil and India display more pronounced variability in their distributions, which is generally associated with greater fluctuations over time. Lastly, Argentina exhibits highly variable distributions with a substantial degree of uncertainty. These disparities in full distributions can be attributed to various economic factors, including structural, cultural, and institutional differences among countries.

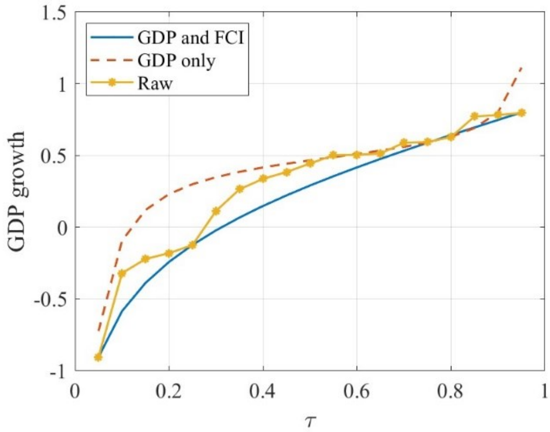
However, considering the focus of this thesis, it is crucial to examine the role of financial conditions. Therefore, I now demonstrate how the inclusion of financial conditions in this model influences the estimates. For this purpose, I illustrate in Figure 10 the raw conditional quantiles of real GDP growth alongside the estimated skewed t-inverse cumulative distributions. These distributions are generated first by conditioning solely on GDP growth and then by incorporating the Financial Conditions Index as a conditioning factor.

Figure 10. Conditional Quantile Distributions of GDP growth, one quarter lag
The panels display conditional quantiles alongside estimated skewed t-inverse cumulative distribution functions for one quarter ahead real GDP growth. The figure includes: the Raw conditional quantiles, the estimated skewed t-inverse cumulative distribution functions for one quarter ahead GDP growth using as conditioning variables the GDP growth only, and the estimated skewed t-inverse cumulative distribution functions using as conditioning variables the GDP growth and the Financial Conditions Index.

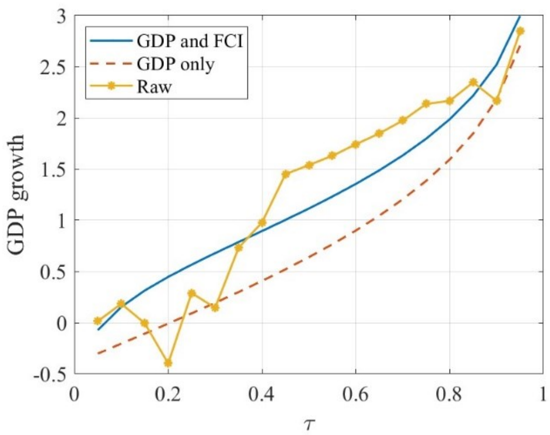
1. US



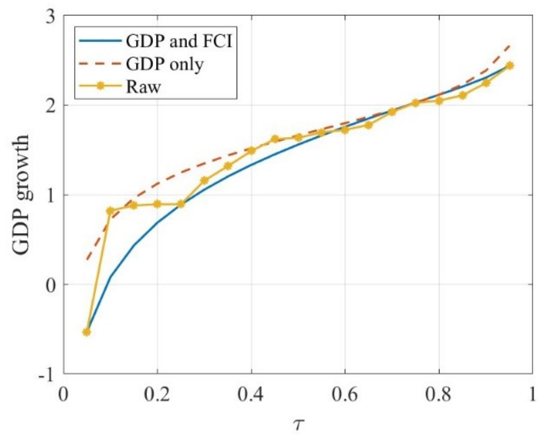
2. Euro Zone



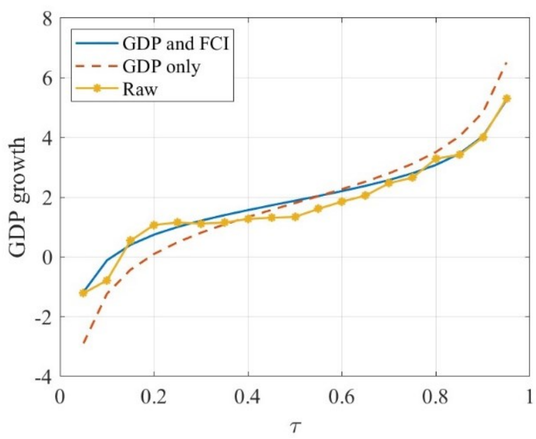
3. Argentina



4. Brazil



5. India

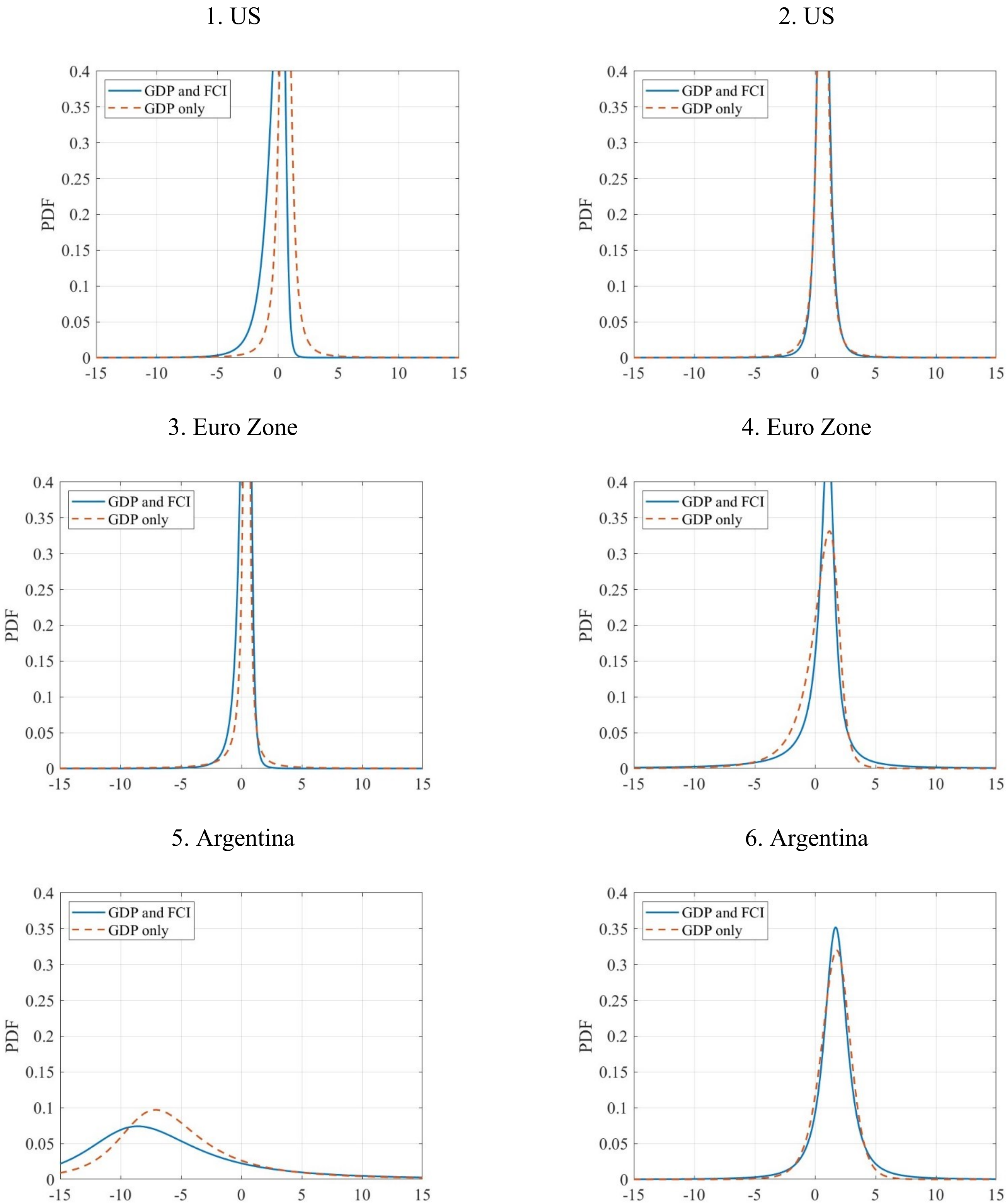


The distinctions observed in each quantile of the estimated skewed t-inverse cumulative distribution functions, both in models considering only GDP growth and those incorporating the Financial Conditions Index, highlight the predictive power of financial conditions when forecasting real GDP growth in each of the analyzed countries.

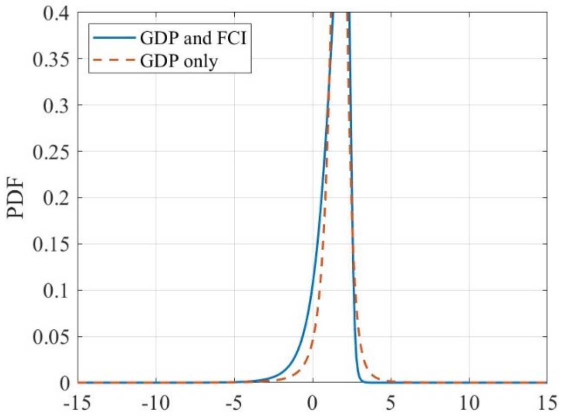
Furthermore, the positive slope of the distribution and the greater disparities between the conditional and unconditional models' distributions in the lower quantiles underscore the significant role of the Financial Conditions Index in predicting particularly unfavorable economic scenarios. Conversely, for each of the country under analysis Financial Conditions appear to have less influence on predicting higher quantiles, indicating the importance of other unexplained factors in forecasting economic activity during periods of significant expansion.

These insights are reflected in the evolving GDP distributions over time. Hence, in Figure 11, I present the probability distribution function of real GDP growth for both models, one with the Financial Condition Index as a conditioning variable and one without. This figure essentially dissects Figure 9 at a specific point in time, enabling a clearer comparison of how financial conditions influenced the estimation in that specific time moment.

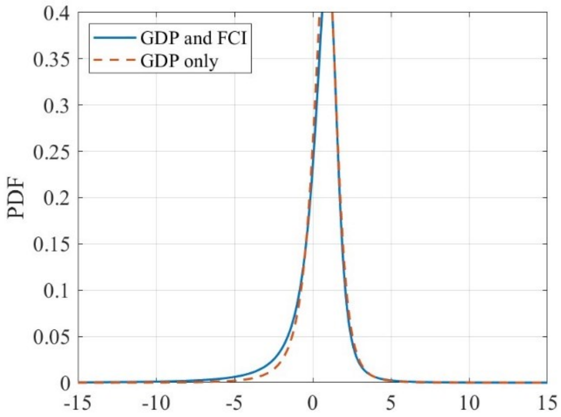
Figure 11. GDP growth probability distribution functions, one quarter model
The panels display the estimated skewed t-density functions for one quarter ahead real GDP growth. The figure includes the estimated skewed t-density functions for one quarter ahead GDP growth using as conditioning variables the GDP growth only, and the same estimated skewed t-density functions using as conditioning variables the GDP growth and the Financial Conditions Index.



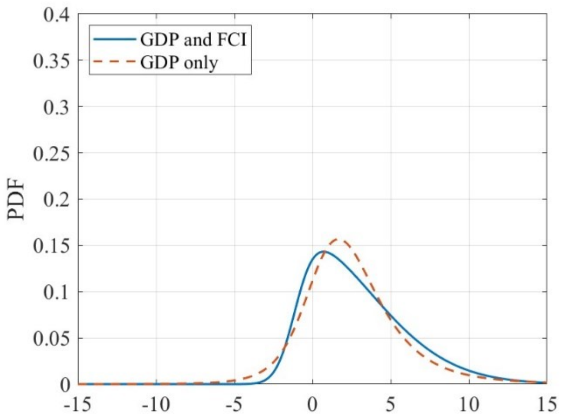
7. Brazil



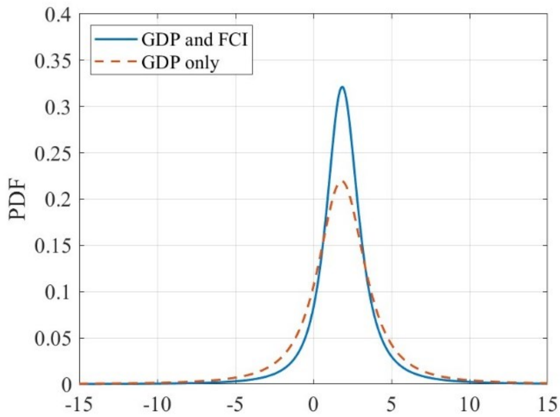
8. Brazil



9. India



10. India



The findings demonstrate the substantial influence of financial conditions on predicting GDP growth, particularly in the lower quantiles. There are generally negligible alterations observed in the right side of the distribution. It is evident that during periods characterized by relatively stable financial conditions, the impact of these conditions on GDP growth estimation is reflected in reduced uncertainty, leading to a decrease in the estimated scale parameter $\hat{\sigma}_{t+h}$.

Conversely, in times of adverse financial conditions, the inclusion of the Financial Conditions Index tends to amplify the distribution's scale $\hat{\sigma}_{t+h}$ and fatness parameter $\hat{\alpha}_{t+h}$, while decreasing the shape parameter $\hat{v}_{t+h}$. This emphasizes the importance of financial conditions as a significant risk factor for economic growth. The subsequent paragraph studies in more detail this relationship, giving a more precise definition of the risks associated with GDP growth.

2. Risk Measures Estimation

Once estimated the entire distribution of real GDP growth using the aforementioned methodology, I am now interested in measuring the risks associated with these estimates. For this reason, I compute two measures to assess the forecasted path of GDP growth to unexpected shocks, according to the work of Adrian et al. (2019).

For these measures, I compare the probability of extreme values in the left and right tail of the distribution for the density function of the skewed t-distribution conditioning on GDP growth alone with the values for the conditional density function $\hat{g}_{y_{t+h}}$, which is constructed by smoothing the GDP growth time series on the estimate skewed t-distribution, by conditioning also on financial conditions. The excess probability of the conditional density with respect to the unconditional one represents the excess vulnerability of forecast in the GDP growth distribution around the central value added by fitting financial conditions variables to the unconditional distribution.

2.1 Upside and Downside Entropy

The first measure proposed to evaluate risks associated with the predicted GDP growth path is the relative entropy, named as Upside Entropy $\mathcal{L}_t^U$ for the extra probability mass in the upside tail, and $\mathcal{L}_t^D$ for the extra probability mass in the downside tail. These are defined as:

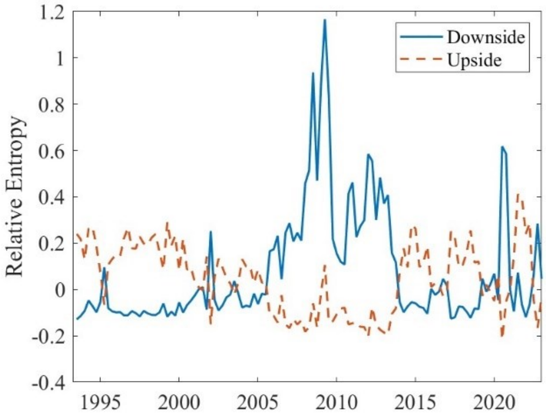
$$\mathcal{L}_t^U\left(\hat{f}_{y_{t+h}|x_t}; \hat{g}_{y_{t+h}}\right) = -\int_{\hat{F}^{-1}{}_{y_{t+h}|x_t}(0.5|x_t)}^{\infty} \left(\log \hat{g}_{y_{t+h}}(y) - \log \hat{f}_{y_{t+h}|x_t}(y|x_t)\right)\hat{f}_{y_{t+h}|x_t}(y|x_t)dy$$

$$\mathcal{L}_t^D\left(\hat{f}_{y_{t+h}|x_t}; \hat{g}_{y_{t+h}}\right) = -\int_{-\infty}^{\hat{F}^{-1}{}_{y_{t+h}|x_t}(0.5|x_t)} \left(\log \hat{g}_{y_{t+h}}(y) - \log \hat{f}_{y_{t+h}|x_t}(y|x_t)\right)\hat{f}_{y_{t+h}|x_t}(y|x_t)dy$$

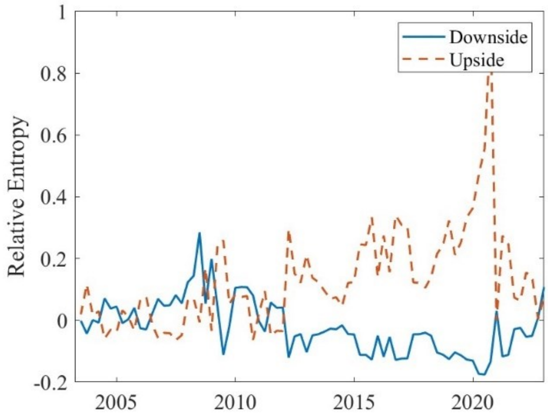
Where $\hat{g}_{y_{t+h}}$ represents the unconditional distribution of GDP growth, $\hat{f}_{y_{t+h}|x_t}(y|x_t) = f(y; \hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{v}_{t+h})$ the skewed t-distribution associated, and $\hat{F}^{-1}{}_{y_{t+h}|x_t}(0.5|x_t)$ is the conditional median. Given this characterization, the Upside Entropy $\mathcal{L}_t^U$ is high when the conditional density attributes a greater likelihood to observe a value in the right tail of the distribution with respect to the unconditional density. Whether the downside Entropy $\mathcal{L}_t^D$ is high when the conditional density attributes a greater likelihood to observe a value in the left tail of the distribution with respect to the unconditional density. The estimated values for both downside and upside entropy are plotted in Figure 12.

Figure 12. Upside and Downside Entropy Estimates, one quarter lag model
The panels show the estimated measures of Upside and Downside Entropy $\mathcal{L}_t^U$ and $\mathcal{L}_t^D$ of GDP growth around the median for each of the country analyzed. These measures are computed over the one quarter lag model results.

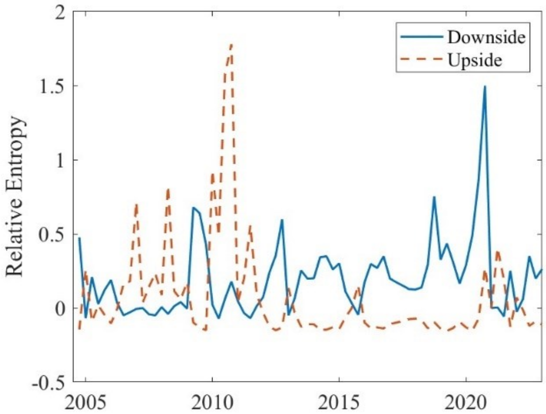
1. US: one quarter lag model



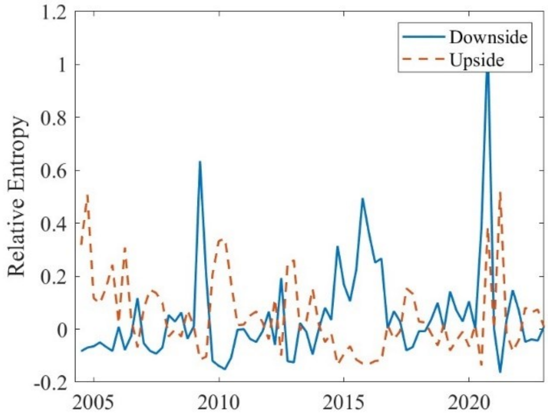
3. Euro Zone: one quarter lag model



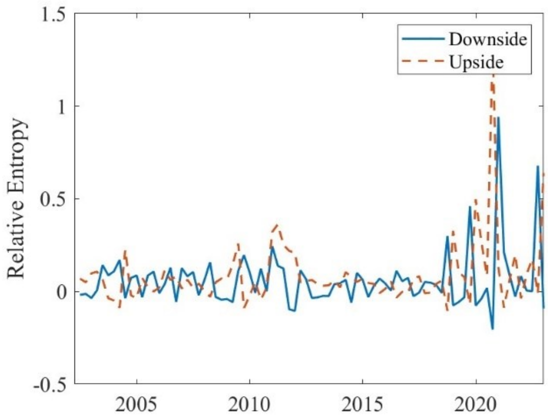
5. Argentina: one quarter lag model



7. Brazil: one quarter lag model



9. India: one quarter lag model



2.2 Expected Long-Rise and Expected Short-Fall

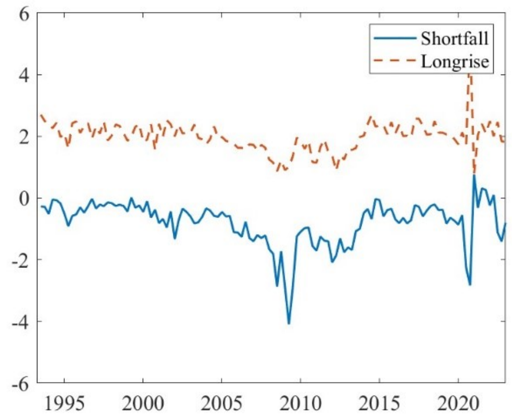
The second methodology used to measure the risks to GDP growth is Expected Short-Fall SF_{t+h} and Expected Long-Rise LR_{t+h}. By defining a probability π, the Expected Long-Rise is the expected value of the deviation from the median of GDP growth, given that the value of GDP growth is below the πth percentile of the conditional distribution. On the other hand, the Expected Long-Rise is the expected value of the deviation from the median of GDP growth, given that the value of GDP growth is above the (1-πth) percentile of the conditional distribution. These are defined mathematically as:

$$SF_{t+h} = \frac{1}{\pi}\int_0^{\pi} \log \hat{F}^{-1}{}_{y_{t+h}|x_t}(\tau|x_t)\, d\tau \qquad LR_{t+h} = \frac{1}{\pi}\int_{1-\pi}^{1} \log \hat{F}^{-1}{}_{y_{t+h}|x_t}(\tau|x_t)\, d\tau$$

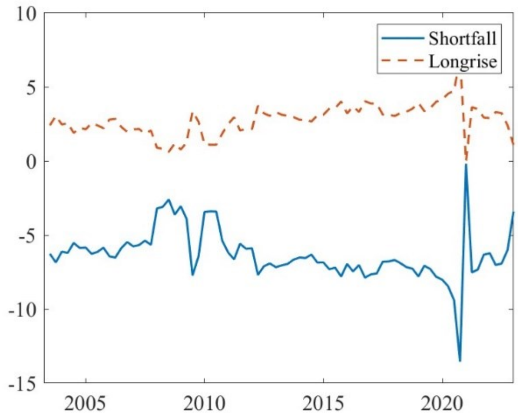
The estimated values for these measures are plotted in Figure 12, given a probability π=5%.

Figure 13. Expected Short-Fall and Long-Rise Estimates, one quarter lag model
The panels display the estimated measures of Expected Short-Fall SF_{t+h} and Expected Log-Rise Rise LR_{t+h} of GDP growth, with a fixed probability π=5%, of each of the analyzed country. These measures are computed over the one quarter lag model results.

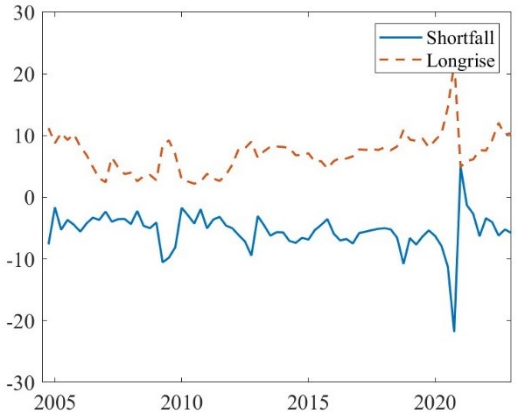
1. US: one quarter lag model



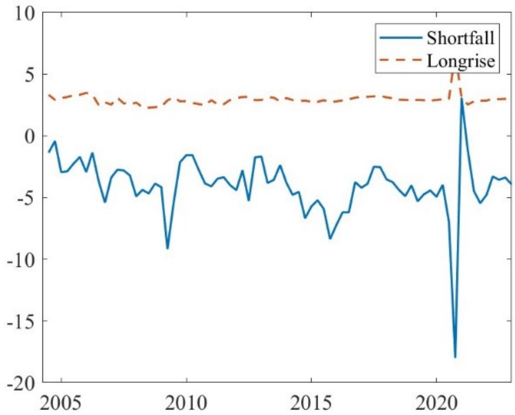
3. Euro Zone: one quarter lag model



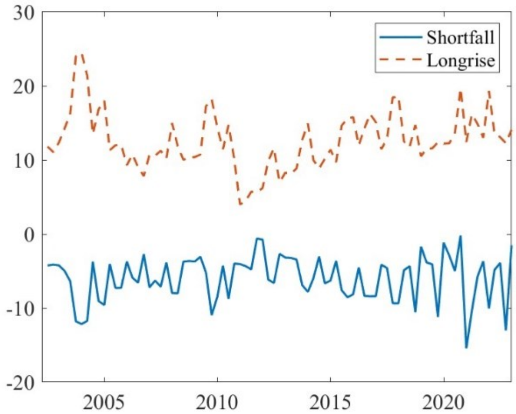
5. Argentina: one quarter lag model



7. Brazil: one quarter lag model



9. India: one quarter lag model



2.3 Results

Despite the disparities in the informational substance of the two measures, they exhibit a notable degree of resemblance. This highlights how the conditional distribution characteristics differ substantially from the unconditional distribution ones, presenting non-Normal characteristics.

Additionally, it is worth mentioning that as upside and downside entropy have a clear positive correlation, also the Expected Short-Fall and Long-Rise measures are positively correlated.

Considering the estimation results discussed in the preceding section, one might anticipate that "positive" risk measures exhibit greater stability over time compared to the "negative" ones. However, it is noteworthy that Expected Short-Fall demonstrates considerably more fluctuations compared to Expected Long-Rise, although this distinction is not as pronounced when examining the entropy measures. Specifically, the average standard deviation of the Expected Shortfall measure for the countries under analysis stands at 2.2173, while its negative counterpart is only 1.8316. Conversely, for the entropy measures, the difference is more modest, with an average standard deviation of 1.990 for downside entropy and 1.880 for the upside counterpart.

Finally, these results show how low realized values of GDP growth coincide with high values of downside risks, highlighting again the importance of financial conditions in forecasting financial conditions, especially in times of financial instabilities.

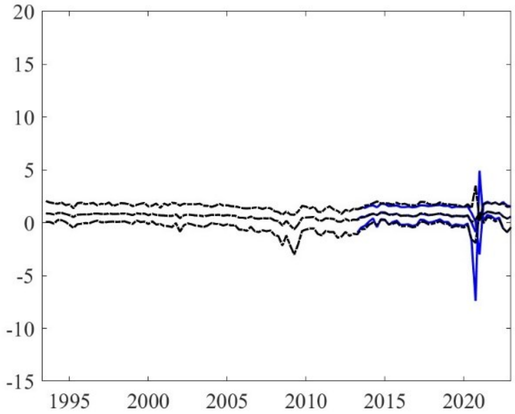
3. Out-of-Sample Evidence

In this section, I evaluate the performance of the proposed methodology by also analyzing its ability to predict out-of-sample. To do this, I back-test the econometric model adopted for each of the country under analysis to produce predictive distributions recursively for the two different time horizons used before: one quarter and one year ahead. I start with an estimation sample that ranges from the beginning of the datasets for each country to the end of 2012 (2012 Q4), to produce precisely 10 years of out-of-sample predictions. Then, for every period ahead I first estimate the out-of-sample prediction using the methodology explained before, and then I replace the predicted value with the realized one, to always have the prediction for one period forward. I predict one period at a time until the end of the sample (2022 Q4). After, I perform two types of analyses to evaluate the accuracy and calibration of the forecasts.

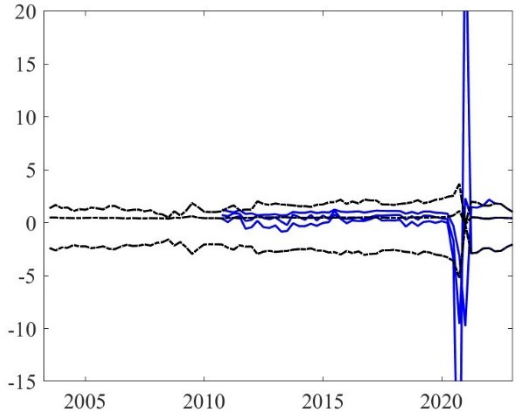
First, I study the robustness of out-of-sample predictions by comparing those with their in-sample equivalent measures. For this purpose, I compare the out-of-sample quantile predictions with the in-sample ones, and the out-of-sample vulnerability measure, represented by downside entropy, with the in-sample counterpart. Figure 13 shows the results of quantile fitting in-sample and out-of-sample for estimates one quarter ahead. Indeed, the estimates for downside entropy are plotted in Figure 14.

Figure 14. Quantile in-sample and out-of-sample predictions comparison, one quarter lag model
The figures compare the in-sample (in black) with the out-of-sample predictions for GDP growth (in blue) one quarter forward. The distribution is predicted at the 5, 50 and the 95 percent quantiles.

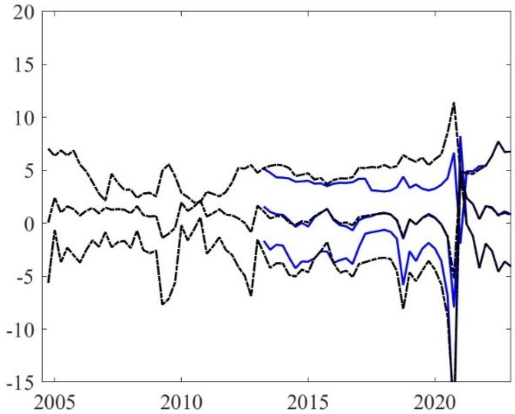
1. US: one quarter lag model



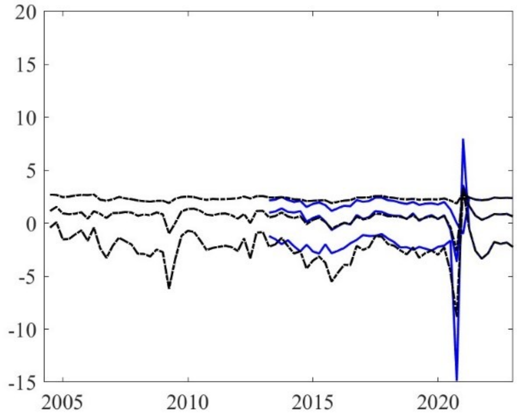
2. Euro Zone: one quarter lag model



3. Argentina: one quarter lag model



4. Brazil: one quarter lag model



5. India: one quarter lag model

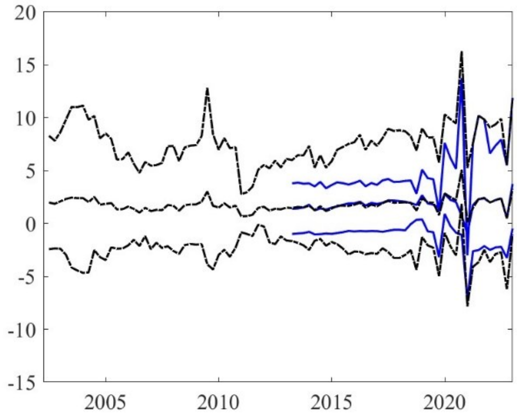
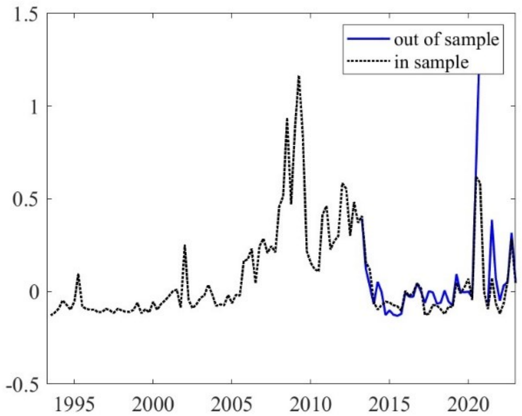
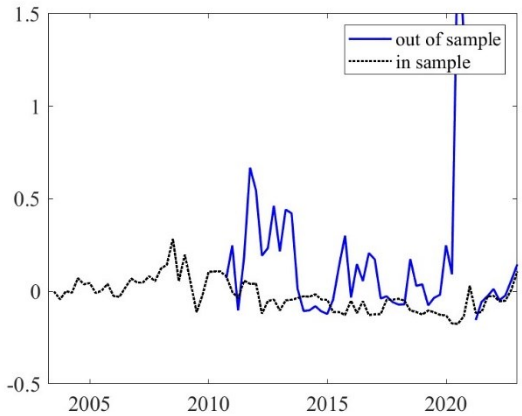


Figure 15. In-sample and out-of-sample downside entropy comparison, one quarter lag model
The figures show the in-sample and out-of-sample predictions for downside entropy measures one quarter forward.

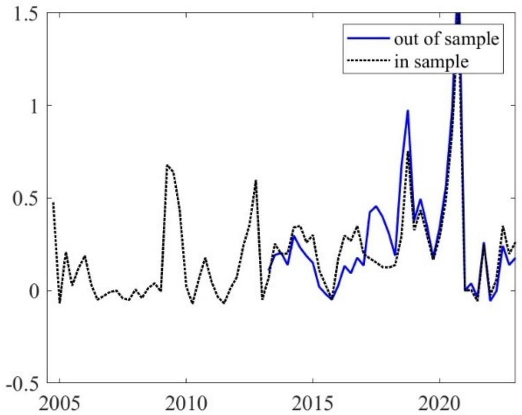
1. US: one quarter lag model



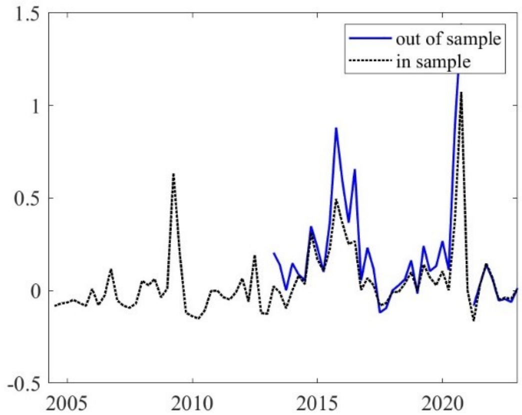
2. Euro Zone: one quarter lag model



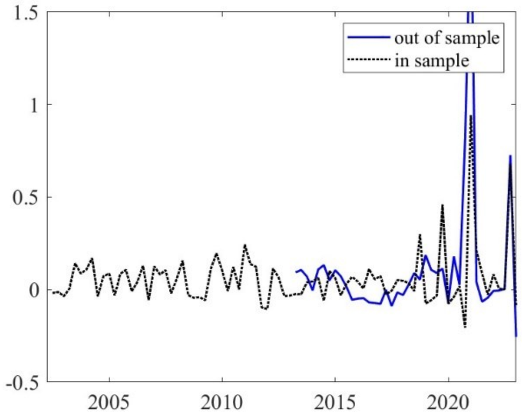
3. Argentina: one quarter lag model



4. Brazil: one quarter lag model



5. India: one quarter lag model



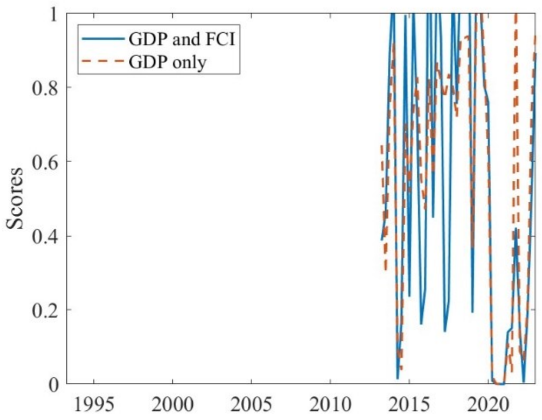
The quantile out-of-sample predictions closely follow the in-sample ones, suggesting the high predictive power of the models. Moreover, it is important to notice how for the low quantiles, the performance is generally better for predictions in the lower quantile (5^{th} percent quantile) and in the median with respect to the high quantiles, which present generally a smoother distribution. Furthermore, the downside entropy out-of-sample estimates present an impressive performance, suggesting the importance of financial conditions in predicting in real time economic vulnerabilities. The Euro Zone stands as the sole exception, displaying less than satisfactory results in terms of entropy estimation. This situation calls for a more in-depth examination to uncover the underlying reasons for this outcome. Several factors may have influenced this estimation, as well as others. These factors could include the relatively short time horizon used for computing the initial in-sample predictions, with an average of only 47 observations. This limited dataset could have adversely affected model accuracy. Additionally, the presence of a significant outlier event like the Covid-19 pandemic in 2020 might have distorted the estimation process. However, despite these specified limitations, the results remain highly convincing, especially when considering out-of-sample performance.

Now, I proceed to evaluate the accuracy and calibration of the density forecasts using the predictive scores and the probability integral transform (PITs), which represent respectively the predictive density and the cumulative distribution of the data when evaluated recursively to the last estimated period. The purpose in this case is to compare the out-of-sample performances for the model with the only lagged GDP growth as regressor and the one with both GDP growth and Financial Conditions as regressors. The predictive scores, in particular, measure the probability to observe the realized value of GDP growth given the iterative model predicted distribution, the scores are plotted including both the estimates using both the model with only lagged GDP growth as regressor and including also the lagged Financial Conditions Index in Figure 16.

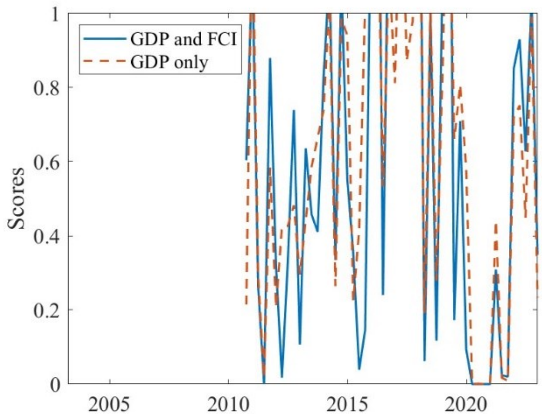
Finally, I evaluate the accuracy of the predictive distribution through the examination of the empirical cumulative distribution of Probability Integral Transformations (PITs). PITs represent the percentage of observations below a specific quantile. Figure 17 displays the PITs values plotted against the 45-degree line. In an ideally calibrated model, the PITs would align precisely with this line. As a general guideline, the closer the PITs are to the line, the more accurate the estimates. Additionally, confidence bands are included around the 45-degree line to address sample uncertainty, following Rossi and Sekhposyan (2017).

Figure 16. Out-of-sample Predictive Scores, one quarter lag model
The figures show the out-of-sample predictive scores for GDP growth one quarter forward for the model using solely lagged GDP growth as regressor and the model including GDP growth and the FCI.

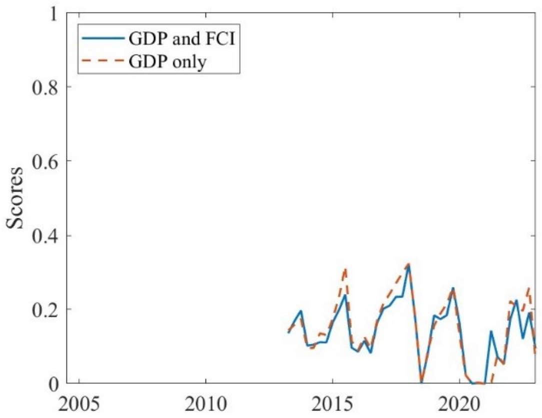
1. US: one quarter lag model



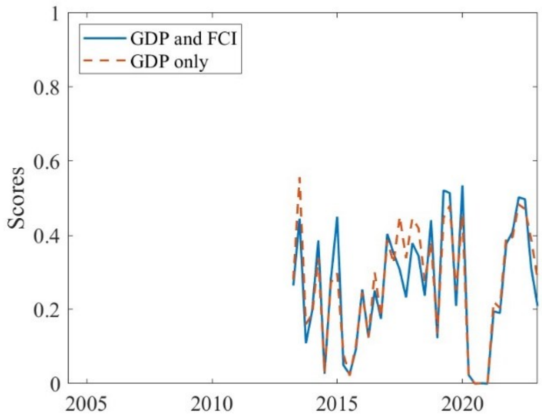
2. Euro Zone: one quarter lag model



3. Argentina: one quarter lag model



4. Brazil: one quarter lag model



5. India: one quarter lag model

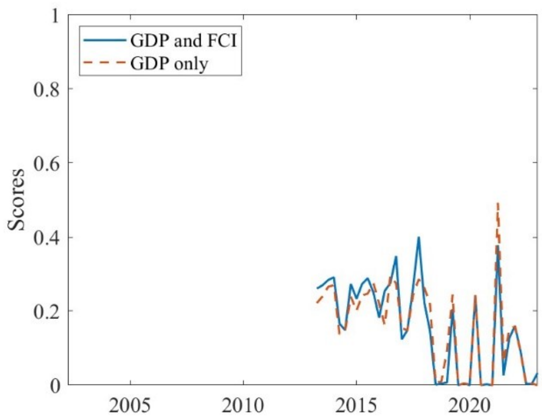
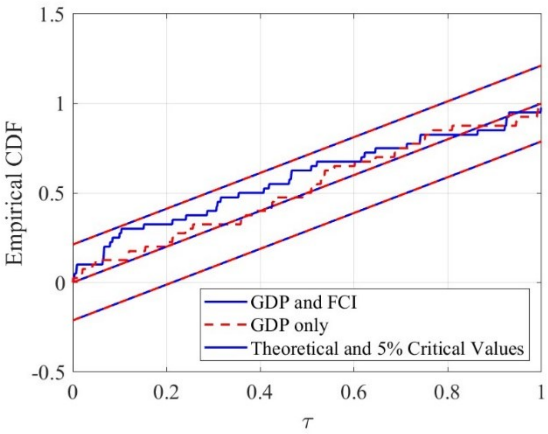
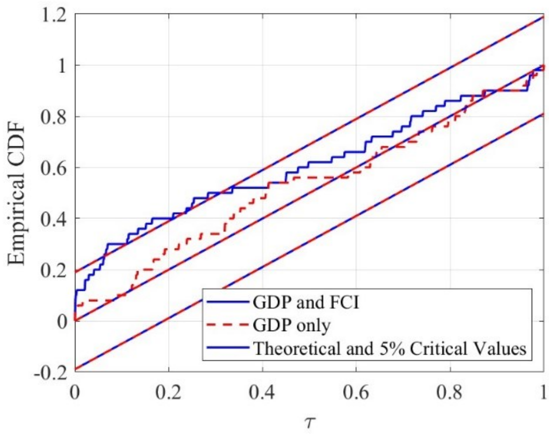


Figure 17. Out-of-sample empirical cumulative distribution of PITs, one quarter lag model
The figures show the empirical cumulative distribution of the PITs for GDP growth one quarter forward for the model using solely lagged GDP growth as regressor and the model including both GDP growth and the FCI as regressors. The PITs represent the percentage of observations under any given quantile. In a perfect calibrated model, the PITs coincide with the 45-degree line.

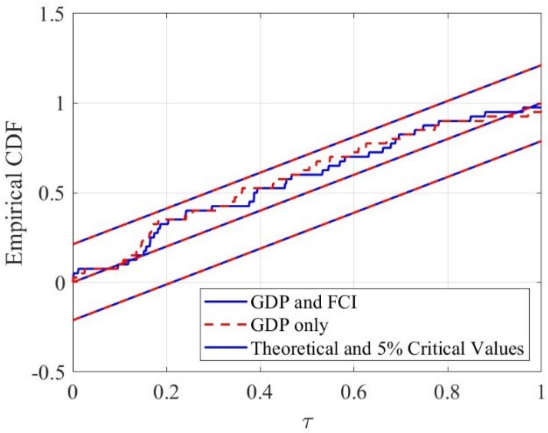
1. US: one quarter lag model



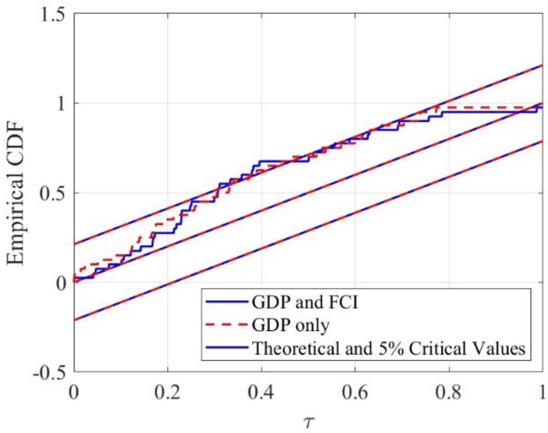
2. Euro Zone: one quarter lag model



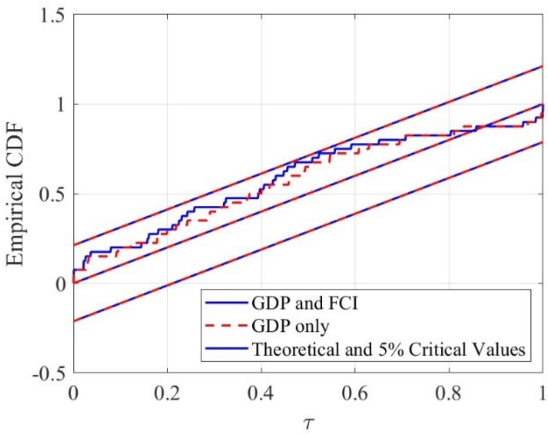
3. Argentina: one quarter lag model



4. Brazil: one quarter lag model



5. India: one quarter lag model



The scores show a slightly higher performance for the models in which financial conditions are included as regressors, especially in the model with one year lag. However, in both models with one quarter and one year lag on average the scores are not significantly different from each other between the model with GDP growth only as regressor and the one including also the Financial Conditions Index.

The graph effectively demonstrates the accurate calibration of the models when estimating different quantiles of the distribution. The probability integral transforms (PITs) consistently align with the confidence bands, indicating their reliability. Furthermore, although the improved accuracy of the models incorporating financial conditions as regressors may not be immediately evident, there is a noticeable rise in the proportion of estimates in the lower quantiles compared to the model relying solely on GDP. Consequently, the model exhibits a heightened level of prudence when evaluating potential vulnerabilities, thereby adopting a more conservative stance.

In summary, despite the limited availability of initial data and the presence of an outlier event like the 2020 Covid pandemic in the selected time series, which impacted all the examined countries, these out-of-sample measurements are quite useful to affirm the robustness of the predictive distributions and their ability to correctly capture the negative risks for GDP growth in real time, standing as a valuable tool for policymakers.

V. Conclusions & Monetary Policy Implications

This thesis develops a robust index to summarize financial conditions across a diverse range of countries, including the United States, the Euro Zone, Argentina, Brazil, and India. It explores the effect of financial conditions and the distribution of real GDP growth over time. Importantly, I have demonstrated how GDP growth distribution exhibits significant fluctuations over time and diverges between developed and developing economies.

These findings corroborate the insights offered by Adrian et al. (2019), who emphasize the strong relationship between financial conditions and GDP growth in the United States. Furthermore, this thesis extends their discoveries by emphasizing the significance of this relationship not only in the Euro Area but also in developing economies such as Argentina, Brazil, and India. It illustrates that, particularly in developing economies and Argentina principally, tight financial conditions are linked not just to lower average GDP growth but, more importantly, to less resilient growth and more uncertain GDP growth.

This suggests that traditional macroeconomic models, which rely on linear approximations, may not adequately capture the empirical distribution of GDP growth. Instead, non-linear models may be more suitable. By integrating financial variables into macroeconomic models, we can enhance forecast accuracy and gain valuable insights into the complex relationship between financial conditions and economic performance.

This discovery underscores the importance of acknowledging the dynamic interplay between financial conditions and the broader economy in all the analyzed countries. Conventional macroeconomic models often overlook the influence of financial variables and assume a linear relationship between financial conditions and GDP growth. However, by considering the higher moments of GDP growth and recognizing the impact of non-linearities resulting from financial conditions, we can develop more resilient models that better reflect the empirical distribution of economic outcomes.

Financial conditions, indeed, have a profound effect on GDP growth, particularly in terms of the uncertainty surrounding the central value and the likelihood of extreme negative (tail) realizations. This effect is crucial for rigorously assessing the risks to which economies are exposed, as measured in this thesis through Upside and Downside Entropy, Expected Short-Fall, and Expected Long-Rise measures. The thesis has underscored the pivotal role of financial conditions in signaling vulnerabilities in economic growth, especially during periods of tight financial conditions and in developing economies, both within the sample and in out-of-sample assessments.

Given this renewed role of financial conditions, it is crucial to consider the resulting implications for macroeconomic policymaking. If it is evident that while monetary policy plays a vital role in achieving objectives such as price stability, it also exerts significant effects on financial conditions, which in turn can adversely impact future GDP growth and expose it to heightened risks. The trade-off policymakers face is therefore a delicate equilibrium game. Finding the right balance between short-term objectives and long-term policy implications for financial conditions and GDP growth requires a comprehensive understanding of the economic landscape, robust models for forecasting, and a structured approach to policy implementation. To navigate this trade-off successfully, policymakers must carefully consider a range of factors. They need to continuously assess the state of financial conditions, and evaluate the potential risks associated with their policy decisions on future GDP growth.

In conclusion, I would like to address the limitations of this thesis and propose potential avenues for future research. Firstly, while the simplicity of constructing the Financial Conditions Index has been a notable strength in this study, it also poses a weakness. Improvements are necessary, especially if the index is to be applied for policymaking purposes. Given its pivotal role in the econometric model proposed here, any inaccuracies in capturing a country's financial conditions could potentially invalidate subsequent model results. Looking ahead, further enhancements to this research could involve the inclusion of additional control variables in the model. This would allow for a deeper examination of how financial conditions impact economic activity when accounting for other factors that influence GDP growth over time. For instance, incorporating social and demographic data could provide valuable insights into the complex interplay of variables shaping economic outcomes. These potential refinements could contribute to a more comprehensive understanding of the relationship between financial conditions and economic performance. Nevertheless, the evidence of this relationship in the countries under analysis, considering the challenges of computational complexity and data scarcity, particularly in developing economies, I believe, makes a substantial contribution to the existing literature. I hope it will serve as an important starting point for future research on this topic.

References

Adrian, T., Boyarchenko, N., & Giannone, D. (2019). Vulnerable growth. *American Economic Review*, 109(4), 1263-1289.

Azzalini, A., & Capitanio, A. (2003). Distributions generated by perturbation of symmetry with emphasis on a multivariate skew t-distribution. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 65(2), 367-389.

Bekaert, G., & Harvey, C. R. (2000). Foreign Speculators and Emerging Equity Markets. *Journal of Finance*, 55(2), 565-613.

Berger, A. N., & Bouwman, C. H. (2009). Bank Liquidity Creation. *The Review of Financial Studies*, 22(9), 3779-3837.

Bernanke, B. S., & Gertler, M. (1989). Agency Costs, Net Worth, and Business Fluctuations. *American Economic Review*, 79(1), 14-31.

Bernanke, B. S., & Gertler, M. (1995). Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic perspectives*, 9(4), 27-48.

Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*, 81(3), 637-654.

Campbell, J. Y., & Cochrane, J. H. (1999). By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior. *Journal of Political Economy*, 107(2), 205-251.

Campbell, J. Y., & Vuolteenaho, T. (2004). Bad Beta, Good Beta. *American Economic Review*, 94(5), 1249-1275.

Diamond, D. W., & Dybvig, P. H. (1983). Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy*, 91(3), 401-419.

Estrella, A., & Mishkin, F. S. (1996). The yield curve as a predictor of US recessions. *Current issues in economics and finance*, 2(7).

Forbes, K. J., & Warnock, F. E. (2012). Capital Flow Waves: Surges, Stops, Flight, and Retrenchment. *Journal of International Economics*, 88(2), 235-251.

Gennaioli, N., Shleifer, A., & Vishny, R. W. (2010). Financial innovation and financial fragility.

Gorton, G., & Metrick, A. (2012). Securitized Banking and the Run on Repo. *Journal of Financial Economics*, 104(3), 425-451.

Hamilton, J. D. (1988). Rational-expectations econometric analysis of changes in regime: An investigation of the term structure of interest rates. *Journal of Economic Dynamics and Control*, 12(2-3), 385-423.

Hatzius, J., Hooper, P., Mishkin, F. S., Schoenholtz, K. L., & Watson, M. W. (2010). Financial conditions indexes: A fresh look after the financial crisis (No. w16150). *National Bureau of Economic Research*.

Holton, S., & d'Acri, C. R. (2018). Interest rate pass-through since the euro area crisis. *Journal of Banking & Finance*, 96, 277-291.

Kashyap, A. K., & Stein, J. C. (1995, June). The impact of monetary policy on bank balance sheets. In Carnegie-Rochester conference series on public policy (Vol. 42, pp. 151-195). *North-Holland.*

Koop, G., Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, 71, 101-116.

Krugman, P. (1979). A Model of Balance-of-Payments Crises. *Journal of Money, Credit and Banking*, 11(3), 311-325.

Kuttner, K. N., & Posen, A. S. (2001). The great recession: Lessons for macroeconomic policy from Japan. *Brookings Papers on Economic Activity*, 2001(2), 93-160.

Kuttner, K. N., & Shim, I. (2016). Can non-interest rate policies stabilize housing markets? Evidence from a panel of 57 economies. *Journal of Financial Stability*, 26, 31-44.

Laubach, T., & Williams, J. C. (2003). Measuring the natural rate of interest. *Review of Economics and Statistics*, 85(4), 1063-1070.

Merton, R. C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance*, 29(2), 449-470.

Mishkin, F. S. (1995). Symposium on the Monetary Transmission Mechanism. *Journal of Economic Perspectives*, 9(4), 3-10.

Montagnoli, A., & Napolitano, O. (2005). Financial Condition Index and interest rate settings: a comparative analysis. *Institute of Economic Studies Working Paper*, 8, 2005.

Obstfeld, M., & Rogoff, K. (1996). Foundations of International Macroeconomics. *MIT Press*.

Rajan, R. G. (1994). Why Bank Credit Policies Fluctuate: A Theory and Some Evidence. *The Quarterly Journal of Economics*, 109(2), 399-441.

Reinhart, C. M., & Rogoff, K. S. (2010). Growth in a Time of Debt. *American Economic Review*, 100(2), 573-578.

Rossi, B. and T. Sekhposyan (2010): Have economic models' forecasting performance for US output growth and inflation changed over time, and when?. *International Journal of Forecasting*, 26, 808–835.

APPENDIX 1. Data presentation

In this section, I provide further details about the variables used in the construction of the Financial Conditions Index for the US. The potential variables to be considered for the calculation of the financial conditions index, chosen due to their significance in illuminating the state of economic financial conditions, can be categorized into 8 groups of variables. These variables are all based on quarterly data, with their specific time frames varying depending on the economy under scrutiny. Specifically, the analysis covers the United States from 1993.Q1 to 2022.Q4 (120 observations), the Euro Zone from 2003.Q1 to 2022.Q4 (80 observations), Argentina from 2004.Q2 to 2022.Q4 (75 observations), Brazil from 2004.Q1 to 2022.Q4 (76 observations), and India from 2002.Q1 to 2022.Q4 (84 observations). All of these are presented in constant prices to eliminate the impact of inflation-related trends in the data. At this point, I proceed to enumerate all the original variables utilized in my thesis. Following that, I provide a general overview of the informative nature of each group of variables in shedding light on financial conditions.

1. Data Presentation

Within this section, I enumerate the variables employed in creating the various US Financial Conditions Indexes. These variables are categorized into eight groups, encompassing all conceivable channels through which financial markets can impact a nation's economic activity. These groups include the credit market, bond market, equity market, and exchange rates market. The variables subjected to analysis are as follows:

1. Total Credit Outstanding
    - Consumer Credit Outstanding
    - Commercial and Industrial Loans Outstanding
    - Commercial and Individual Loans Outstanding
    - Loans and Leases in Bank Credit Outstanding

2. Credit Risk Premium
    - Average Credit Risk Premium in Banking System (Prime Rate – Government Bond Rate (10 Years Maturity))

3. Interbanking System Interest Rates
    - Interbank Uncollateralized Overnight Rate

- Interbank Uncollateralized 3 Months Rate
- Interbank Repo Overnight Rate
- Interbank Repo 3 Months Rate

4. Banking System Credit Risk Provisions
   - Total Provisions for loans losses

5. Public Debt
   - Total Gross Public Debt
   - Gross Public Debt-GDP ratio

6. Exchange Rates
   - Effective Exchange Rate

7. Equity Volatility & Equity Risk Premium
   - MSCI World Volatility (5 Years Variance)
   - SP500 Volatility (5 Years Variance)
   - Equity Risk Premium

8. Government Bond Yield Maturity Spread
   - Government Bond Yield Maturity Spread (10 Years – 1 Year)
   - Government Bond Yield Maturity Spread (10 Years – 3 Months)
   - Government Bond Yield Maturity Spread (1 Year – 3 Months)
   - Government Bond Yield Maturity Spread (30 Years – 3 Months)

2. Data Theoretical Relevance

After enumerating the variables under consideration for potential inclusion in the calculation of the US Financial Conditions Index (US NFCI), I proceed to elucidate the rationale behind their incorporation within each macro-category of variables. Within this framework, I expound upon the theoretical foundations that support the inclusion of these variables. By aligning these variables with the dynamics encapsulated by the official US NFCI, this approach aims to capture the intricate interplay of factors influencing the economies financial stability.

1. The Total Credit Outstanding is an encompassing macrofamily that spans the entirety of credit within the economy, including Consumer Credit Outstanding, Commercial and Industrial Loans Outstanding, Commercial and Individual Loans Outstanding, as well as Loans and Leases in Bank Credit Outstanding. This comprehensive measure emerges as a compelling variable to approximate favourable financial conditions. It captures the overall availability of credit across various economic sectors, providing valuable insights into the accessibility of funds for both businesses and consumers. The intricate interplay between credit availability and economic activity is well-documented. Bernanke and Gertler (1995) elucidate the crucial role of credit in transmitting monetary policy effects to the real economy. Their research underscores how shifts in credit conditions can amplify or dampen the impact of policy changes on economic output and investment. Furthermore, the study by Kashyap and Stein (1995) delves into the connection between bank lending behaviour, credit supply, and the broader economic environment. The dynamics of the total amount of credit outstanding offer a comprehensive view of financial market health and their potential impact on overall economic vitality, rendering it a robust proxy for assessing prevailing financial conditions.

2. The Credit Risk Premium, specifically defined in my thesis as the Average Credit Risk Premium in the Banking System (measured as the difference between the Prime Rate and the Government Bond Rate with a 10-year maturity), assumes a pivotal role in evaluating favourable financial conditions. This metric encapsulates the supplementary return that creditors require to counterbalance the inherent risk entailed in extending credit, thereby reflecting the perceived creditworthiness of borrowers within the banking domain. This premium operates as an effective barometer of market sentiment and risk inclination. Drawing from the pioneering contributions of Merton (1974) and Black and Scholes (1973), research conducted by Campbell and Vuolteenaho (2004) in their work titled "Bad Beta, Good Beta" elucidates the manner in which credit risk premiums influence asset pricing and the broader financial landscape. The study underscores that fluctuations in credit risk premiums wield substantial influence over investment choices, consumption behaviors, and the overarching economic system. Moreover, the exploration undertaken by Gennaioli, Shleifer, and Vishny (2010) delves into the intricate interplay between credit risk and financial innovation. This examination sheds light on how shifts in credit risk perception can ripple through financial markets. The Average Credit Risk Premium in the Banking System presents a nuanced panorama of credit market dynamics and potential shifts in

investor conviction, thus endowing it with the robustness required to serve as a proxy for evaluating prevailing financial conditions and their potential repercussions on the economic landscape.

3. The Interbanking System Interest Rates emerge as pivotal variables that effectively capture and evaluate prevailing financial conditions. These rates collectively embody the cost at which banks extend and acquire funds within the interbank market, providing a lens into the intricate liquidity dynamics inherent to this critical financial domain. The pioneering research of Diamond and Dybvig (1983) underscores the fundamental role of interbank rates in shaping financial stability and systemic risk. Their work illuminates how fluctuations in these rates can catalyze a chain reaction, impacting banks' ability to meet obligations and potentially leading to wide-ranging disruptions within the market. Additionally, the influential study by Gorton and Metrick (2012) delves into the complex interplay between interbank rates, financial innovation, and the propagation of market contagion. By encompassing a spectrum of interbank rates spanning various durations, including overnight and three-month periods, a comprehensive evaluation of short- and medium-term liquidity conditions becomes attainable. By encapsulating the oscillations in interbank lending rates, these variables furnish invaluable insights into the underlying vitality of financial markets, their resilience, and their potential to reverberate throughout the broader economic landscape. This, in turn, positions them as robust indicators adept at appraising the prevalent financial conditions. The considered interbank rates encompass both the Uncollateralized and Collateralized Interbank Rates, spanning both overnight and three-month maturities.

4. Banking System Risk Provisions emerge as a pivotal variable, offering tangible evidence of robust financial conditions. This metric encapsulates the reserves meticulously set aside by banks to anticipate potential future losses stemming from loans that could potentially default. In essence, it serves as a direct lens into the credit quality of bank portfolios and the perceived risk embedded within the lending ecosystem. A noteworthy contribution by Berger and Bouwman (2009) in "Bank Liquidity Creation" delves into the intricate relationship between credit risk provisions and a bank's ability to foster liquidity and sustain lending operations. The research illuminates how prudent provisioning practices can fortify a bank's stability, consequently augmenting its capacity to stimulate economic growth through lending activities. Furthermore, Rajan's work (1994) highlights the

interconnectedness between credit risk provisions and the broader economic cycle. Rajan's study underscores the pivotal role banks play in adjusting their provisioning strategies in tandem with shifts in economic conditions. These adjustments bear direct implications for credit availability, thereby exerting an influence on the broader economic landscape.

5. Public Debt assumes a paramount role in the evaluation of a nation's fiscal well-being and its consequential impact on financial conditions. The metric of Total Gross Public Debt serves as a cumulative representation of a government's historical borrowing endeavours, thereby shedding light on its capacity to manage impending debt commitments. Counterpart to this, the Gross Public Debt-GDP ratio presents an insightful lens through which debt levels are contextualized into the economy's dimension, ultimately providing a nuanced perspective on the tenets of sustainability. Exemplifying this dynamic, the seminal research of Reinhart and Rogoff (2010) unfurls the intricate relationship between elevated public debt and economic growth. Their meticulous analysis underscores a critical threshold within the Gross Public Debt-GDP ratio, beyond which economic growth experiences adverse repercussions. This poignant discovery underscores the potential constraints that intensified debt levels can exert upon a nation's financial conditions and its broader economic performance. Furthermore, the contributions of Laubach and Williams (2015) delve into the interplay between the Gross Public Debt-GDP ratio and its reverberations within the realm of interest rates. Their work illuminates how heightened levels of public debt can potentially exert upward pressure on interest rates, thus influencing the domain of borrowing costs and engendering an impact on the overall fabric of financial conditions. The metrics encapsulated within Public Debt serve as cardinal indicators, effectively conveying facets of fiscal responsibility while unravelling potential macroeconomic vulnerabilities. As instruments of substantial utility, these metrics furnish valuable tools for the discernment of current financial conditions and the attendant implications for the overarching well-being of an economy.

6. Exchange Rates play a pivotal role as the vital conduits linking economies within our increasingly interwoven global landscape. The Effective Exchange Rate, acting as a fulcrum, captures the nuanced weighted average valuation of a nation's currency against a spectrum of other currencies. This incisive metric unveils a profound glimpse into a country's competitive stance within the sphere of international trade. The work authored by Obstfeld and Rogoff (1996) illustrates the impact wielded by fluctuations in exchange rates

upon the intricate interweaving of trade balances and the ebb and flow of capital flows. This compelling study casts light upon the transformative sway of exchange rate dynamics, exerting a discernible impact on the ebbs and flows of export-import dynamics. Furthermore, Krugman (1979) delves into the intricate choreography of exchange rate crises. This seminal inquiry illumines how the ebb and flow of exchange rate fluctuations can cause economic instability, thereby bestowing pertinence upon their capacity to incite disruptions within financial conditions and cast ripples upon the pond of economic growth.

7. Equity Volatility and Equity Risk Premium provide profound insights into the intricate realm of stock market uncertainty and investor sentiment. Volatility measures the intensity of price fluctuations, while the Equity Risk Premium assess the premium investors demand for embracing equities over the safety of risk-free assets. Campbell and Cochrane's study (1999) emerges as a guiding light, illuminating the intricate interplay between risk premiums and the dynamics of consumer behaviour. Their work underscores how shifts in risk premiums cascade through the avenues of investor decisions, not only influencing financial conditions but also the very bedrock of market stability. Also, Bekaert and Harvey's notable composition (2000) lends further resonance to the discourse on equity risk premiums, delving into the interwoven strands that tether foreign speculators to emerging equity markets, weaving a tapestry of understanding that enriches our comprehension of the intricate financial landscape.

8. Government Bond Yield Maturity Spreads[12] offer critical insights into the yield differentials across different time horizons for government bonds. These spreads shed light on market expectations, investor sentiments, and perceived risks associated with various bond maturities. The Government Bond Yield Maturity Spread serves as a leading indicator of financial conditions, often signalling changes in economic expectations and potential shifts in interest rate policies. Research by Estrella and Mishkin (1996) demonstrates the predictive power of the yield curve, particularly the spread between long-term and short-term government bond yields, in forecasting recessions. The study highlights how an inverted yield curve, where short-term yields surpass long-term yields, has historically been associated with economic downturns. This underscores how changes in the Government Bond Yield Maturity Spread can offer insights into evolving financial conditions and their

[12] In my case, I encompass various comparisons such as the 10 Years – 1 Year, 10 Years – 3 Months, 1 Year – 3 Months, and the 30 Years – 3 Months spreads.

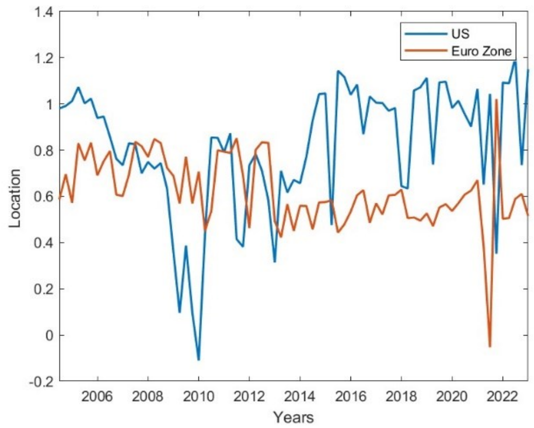
implications for economic performance. Furthermore, research by Hamilton (1988) explores the role of yield spreads in the transmission of monetary policy effects. The study highlights how changes in yield spreads can influence borrowing costs and financial conditions, thereby impacting consumer spending and investment decisions. Government Bond Yield Maturity Spread metrics provide valuable tools for assessing prevailing financial conditions and their potential effects on an economy's overall health, making them pivotal indicators for policymakers and investors.

APPENDIX 2. Figures of One Year Lag Model

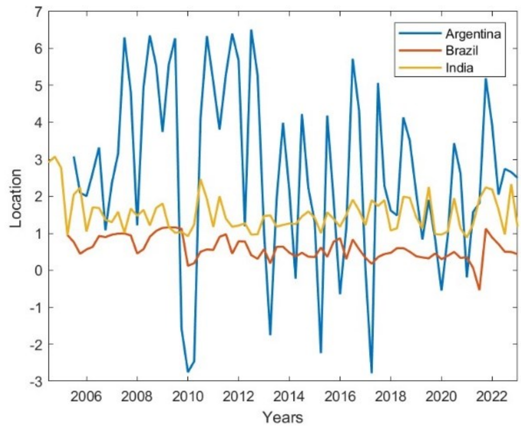
In this section, I present all the figures that for space problems could not be included in the thesis 4th chapter. All these figures refer to the same model discussed in Chapter 4, but with the difference that the model to estimate GDP growth distribution uses as regressors GDP growth itself and the Financial Conditions Index with one year lag.

Figure 8.1. Moments estimates using regressors with one year lag
The panels show the real GDP growth estimated moments $\{\hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h}\}$ smoothing the quantile functions over the skewed t-distribution, for estimates one year ahead (h = 4). The countries are clustered, for visualization purposes, in: Developed Economies (US, Euro Zone) and Developing Economies (Argentina, Brazil, India).
Country: US. Timespan: 1993.Q1 - 2022.Q4. Frequency: Quarterly.
Country: Euro Zone. Timespan: 2003.Q1 - 2022.Q4. Frequency: Quarterly.
Country: Argentina. Timespan: 2004.Q2 - 2022.Q4. Frequency: Quarterly.
Country: Brazil. Timespan: 2004.Q1 - 2022.Q4. Frequency: Quarterly.
Country: India. Timespan: 2002.Q1 - 2022.Q4. Frequency: Quarterly.

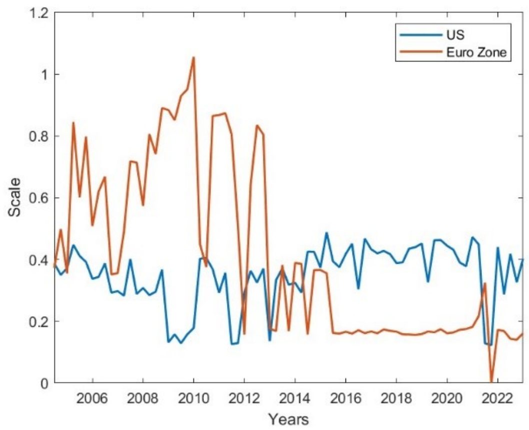
1. Location: Developed Economies



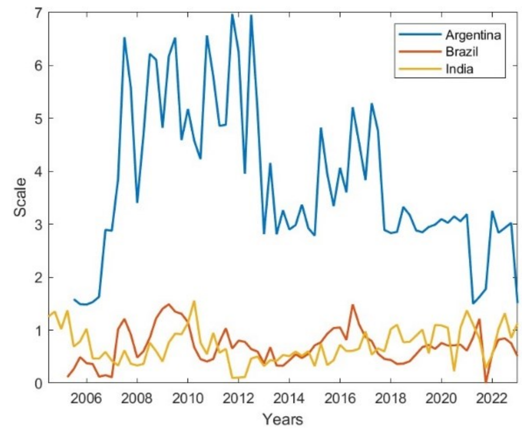
2. Location: Developing Economies



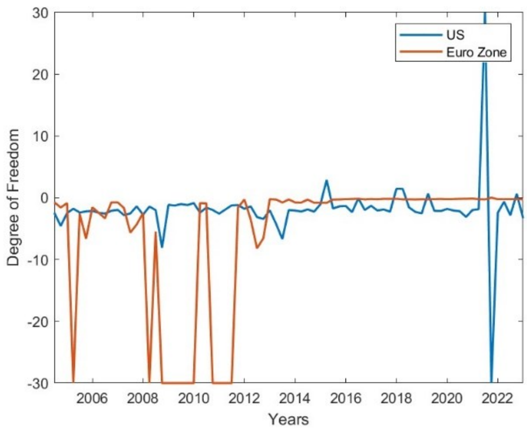
3. Scale:Developed Economies



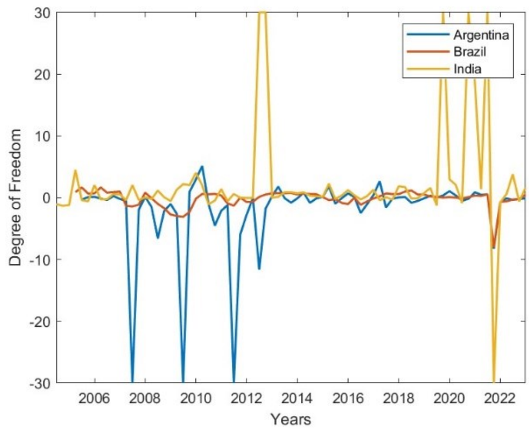
4. Scale: Developing Economies



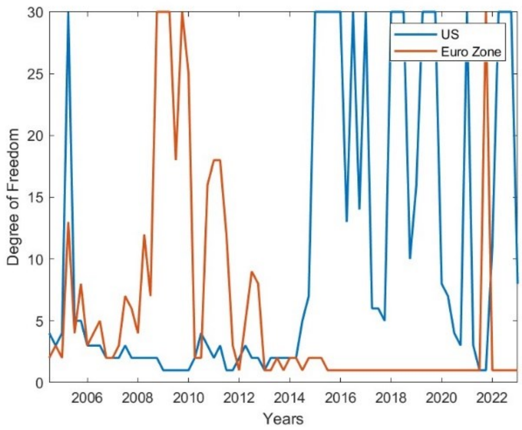
5. Degree of Freedom: Developed Economies



6. Degree of Freedom: Developing Economies



7. Shape:Developed Economies



8. Shape: Developing Economies

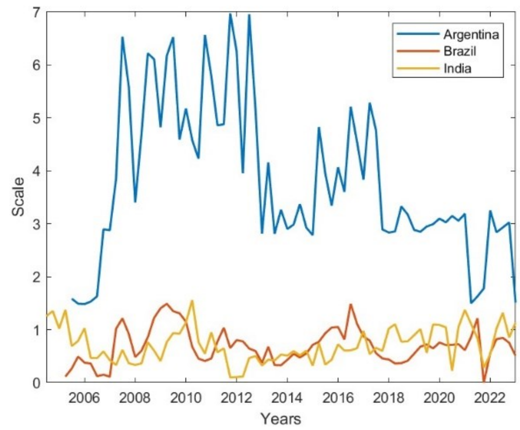
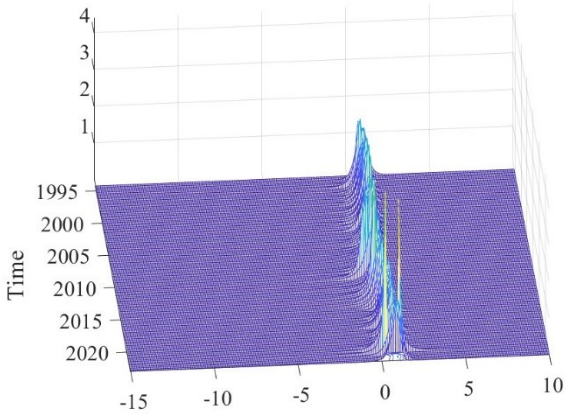
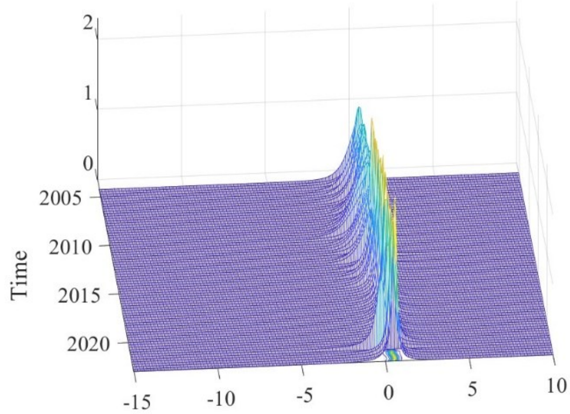


Figure 9.1. GDP growth density distribution, one year lag model
The panels show the one year ahead (h = 4) estimates of real GDP growth full distributions for each of the analyzed country. Estimated using quantile regressions with both real GDP growth and the Financial Conditions Index as independent variables.

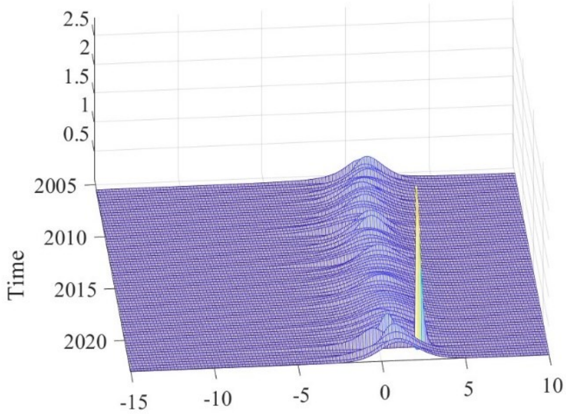
1. US: one year lag model



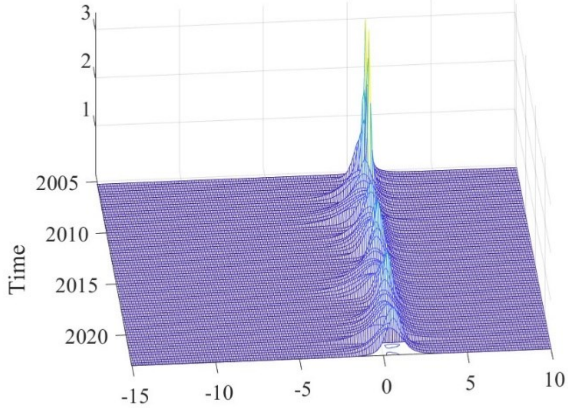
2. Euro Zone: one year lag model



3. Argentina: one year lag model



4. Brazil: one year lag model



5. India: one year lag model

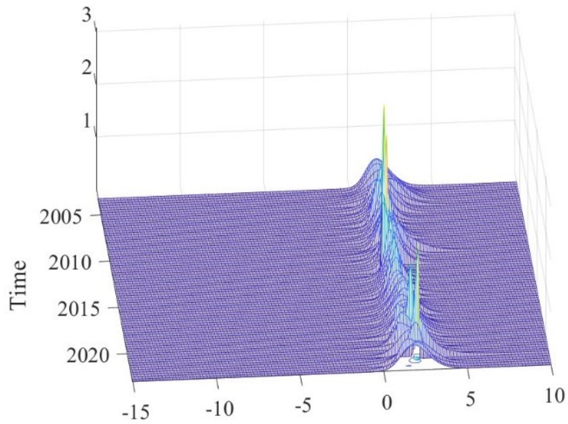
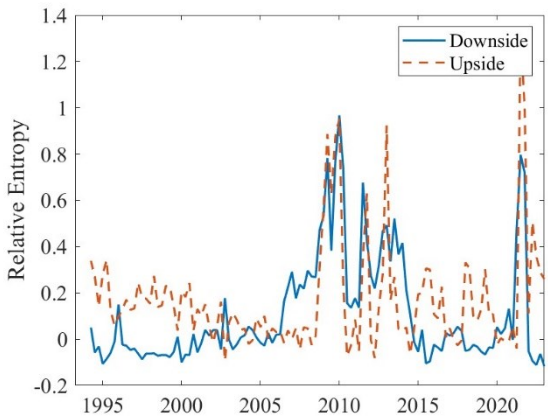
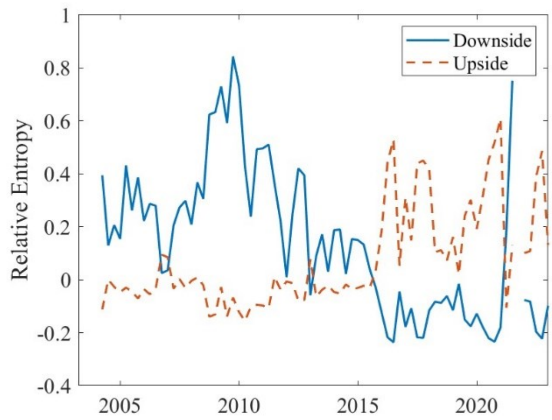


Figure 12.1. Upside and Downside Entropy Estimates, one year lag model
The panels show the estimated measures of Upside and Downside Entropy $\mathcal{L}_t^U$ and $\mathcal{L}_t^D$ of GDP growth around the median for each of the country analyzed. These measures are computed over the one year lag model results.

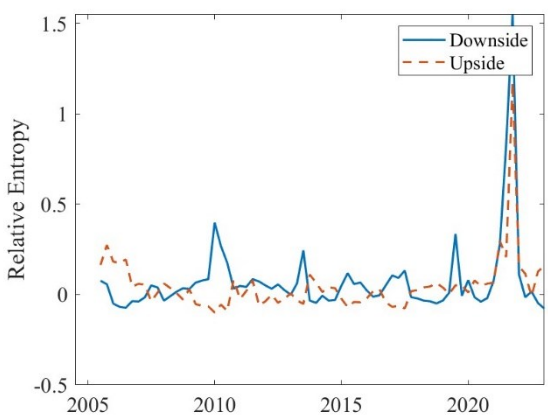
1. US: one year lag model



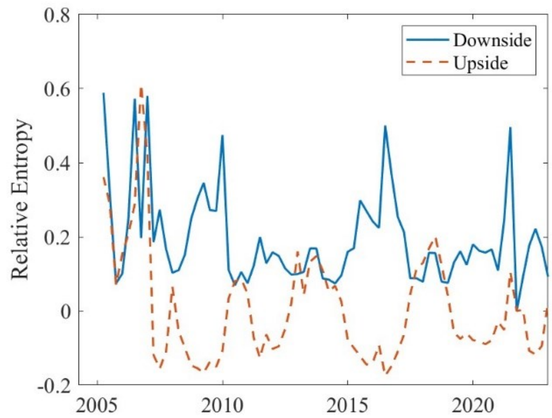
2. Euro Zone: one year lag model



3. Argentina: one year lag model



4. Brazil: one year lag model



5. India: one year lag model

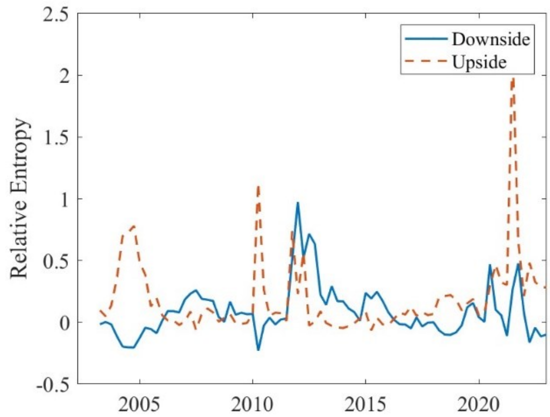
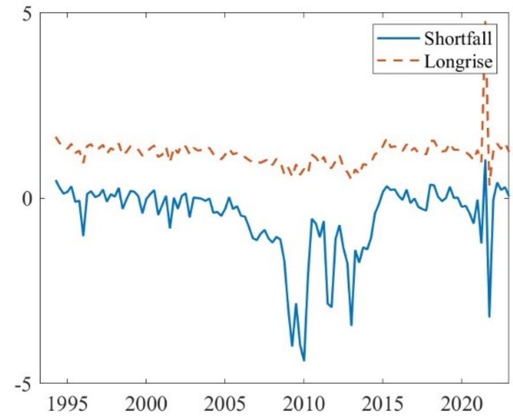
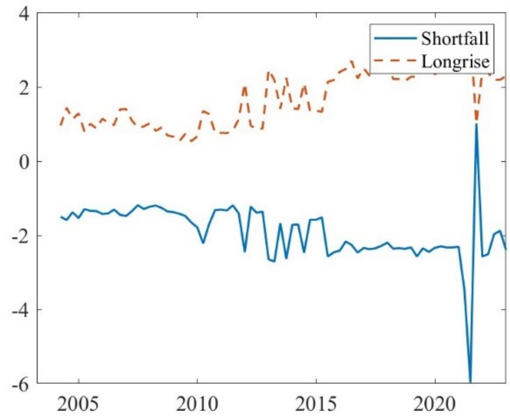


Figure 13.1. Expected Short-Fall and Long-Rise Estimates, one year lag model
The panels display the estimated measures of Expected Short-Fall SF_{t+h} and Expected Log-Rise Rise LR_{t+h} of GDP growth, with a fixed probability π=5%, of each of the analyzed country. These measures are computed over the one quarter lag model results.

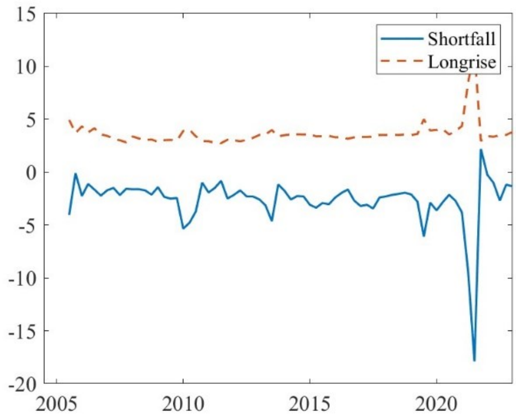
1. US: one year lag model



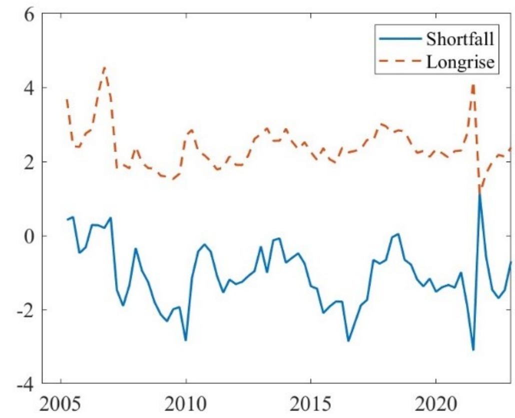
2. Euro Zone: one year lag model



3. Argentina: one year lag model



4. Brazil: one year lag model



5. India: one year lag model

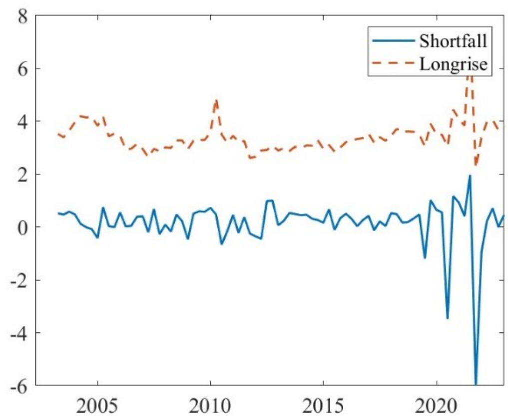
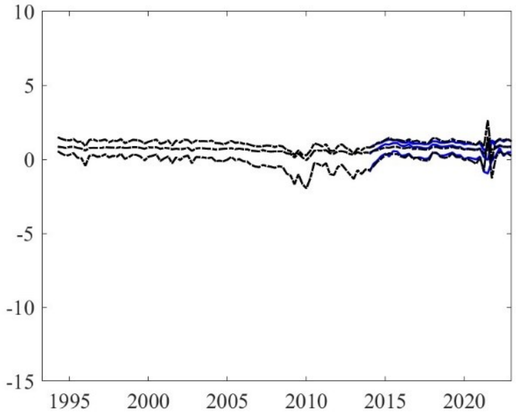
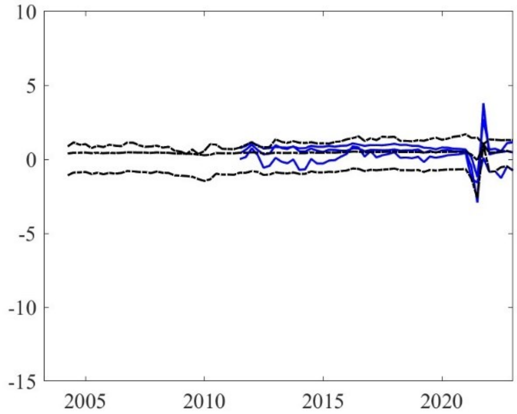


Figure 14.1. Quantile in-sample and out-of-sample predictions comparison, one year lag model
The figures compare the in-sample (in black) with the out-of-sample predictions for GDP growth (in blue) one year forward. The distribution is predicted at the 5, 50 and the 95 percent quantiles.

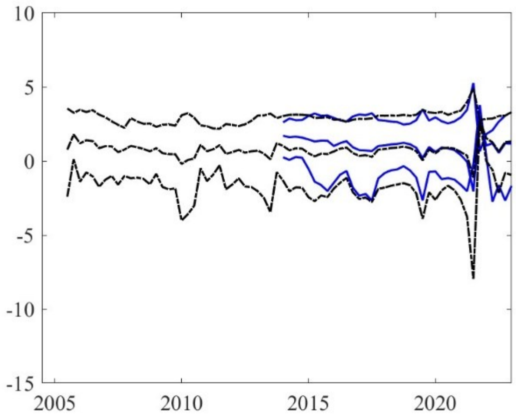
1. US: one year lag model



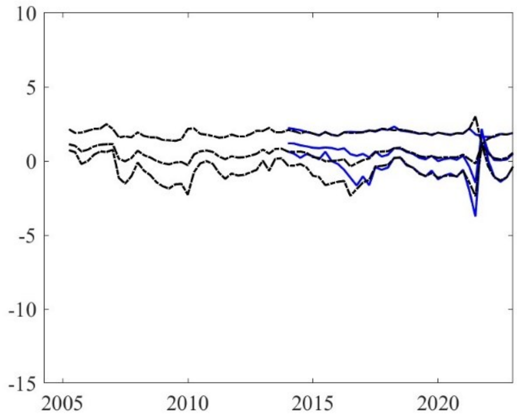
2. Euro Zone: one year lag model



3. Argentina: one year lag model



4. Brazil: one year lag model



5. India: one year lag model

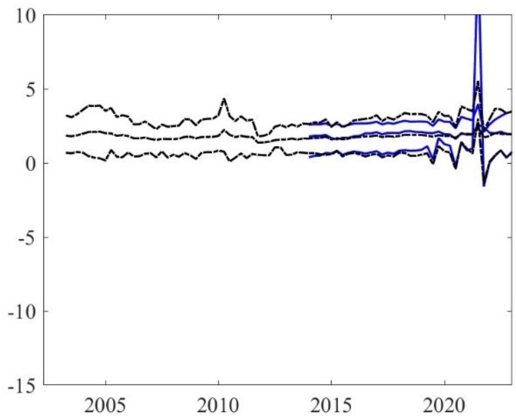
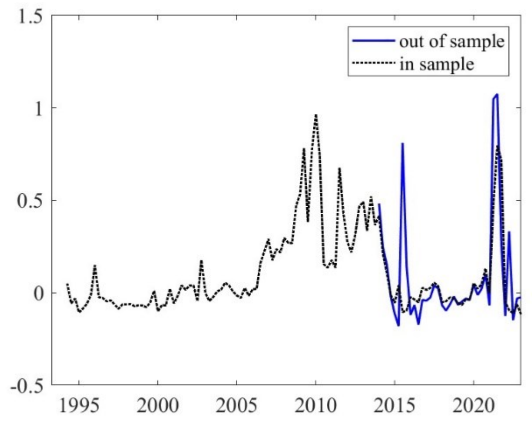
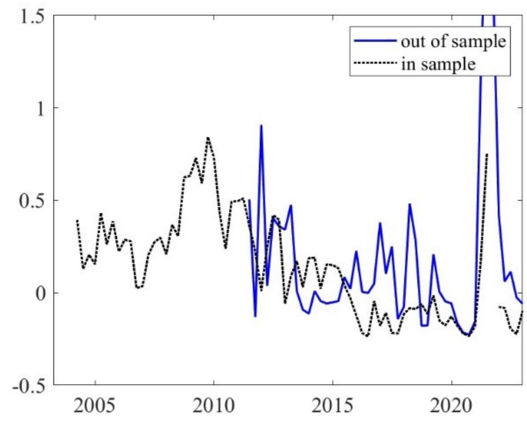


Figure 15.1. In-sample and out-of-sample downside entropy comparison, one year lag model
The figures show the in-sample and out-of-sample predictions for downside entropy measures one year forward.

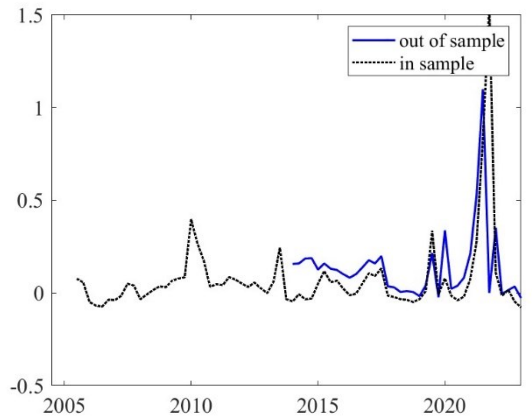
1. US: one year lag model



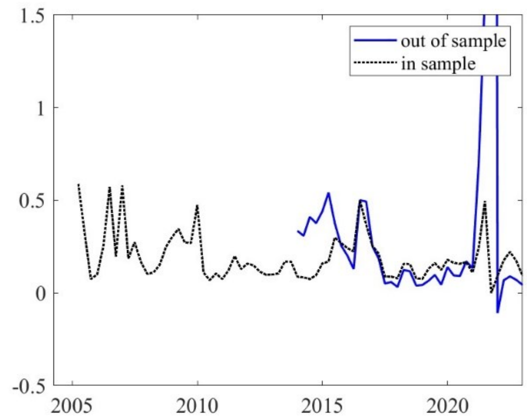
2. Euro Zone: one year lag model



3. Argentina: one year lag model



4. Brazil: one year lag model



5. India: one year lag model

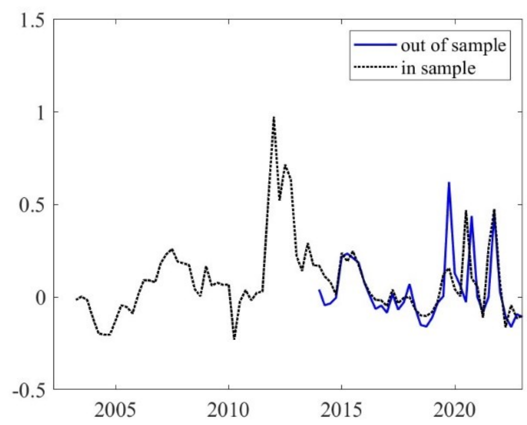
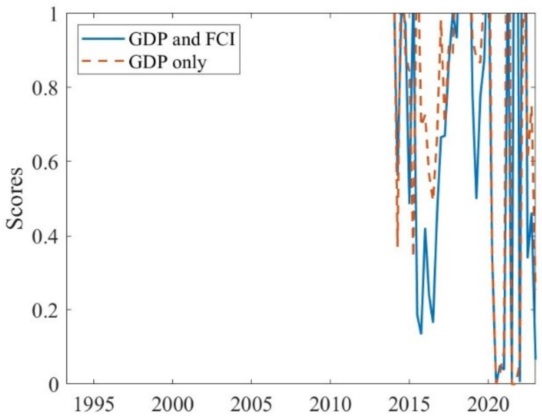
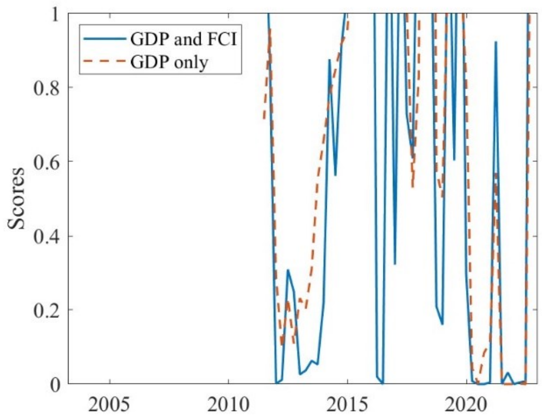


Figure 16.1. Out-of-sample Predictive Scores, one year lag model
The figures show the out-of-sample predictive scores for GDP growth one year forward for the model using solely lagged GDP growth as regressor and the model including GDP growth and the FCI.

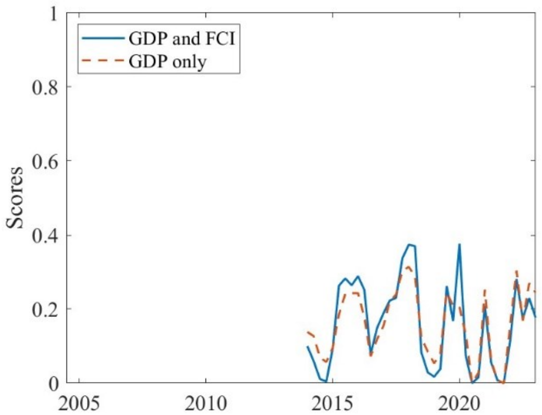
1. US: one year lag model



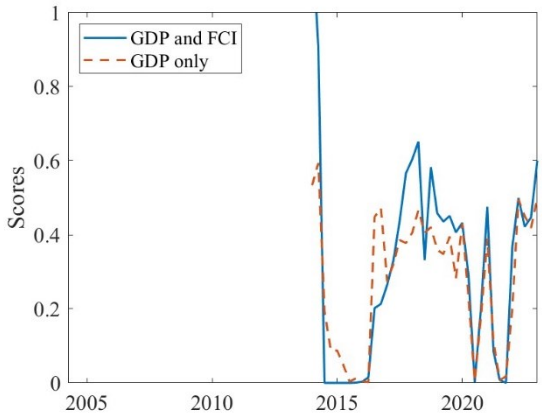
2. Euro Zone: one year lag model



3. Argentina: one year lag model



4. Brazil: one year lag model



5. India: one year lag model

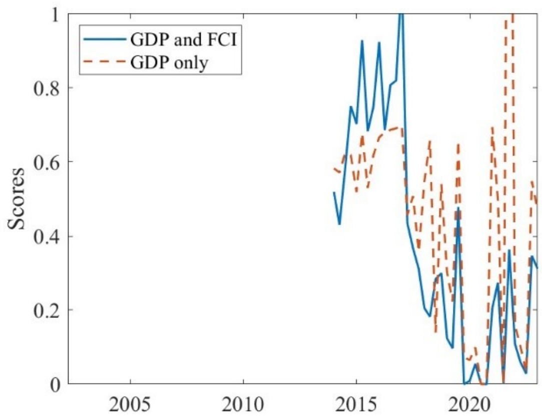
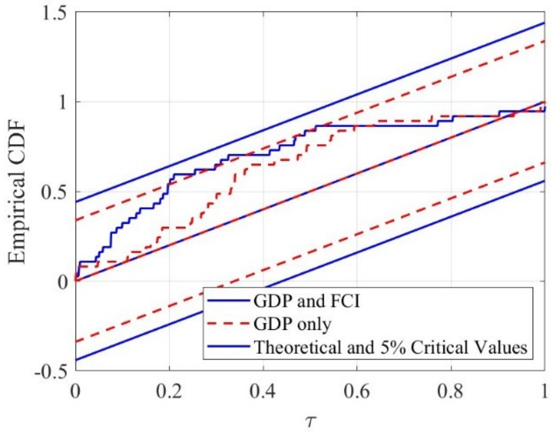


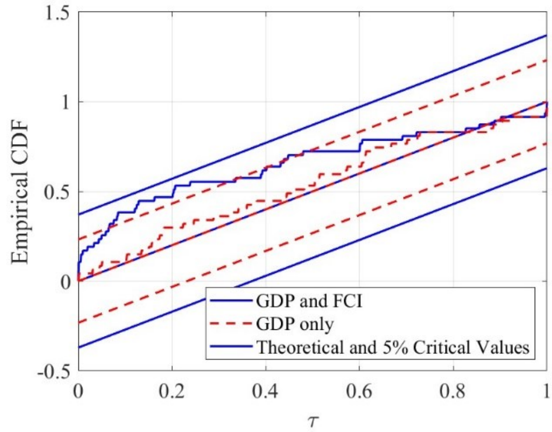
Figure 17.1. Out-of-sample empirical cumulative distribution of PITs, one year lag model

The figures show the empirical cumulative distribution of the PITs for GDP growth one year forward for the model using solely lagged GDP growth as regressor and the model including both GDP growth and the FCI as regressors. The PITs represent the percentage of observations under any given quantile. In a perfect calibrated model, the PITs coincide with the 45-degree line.

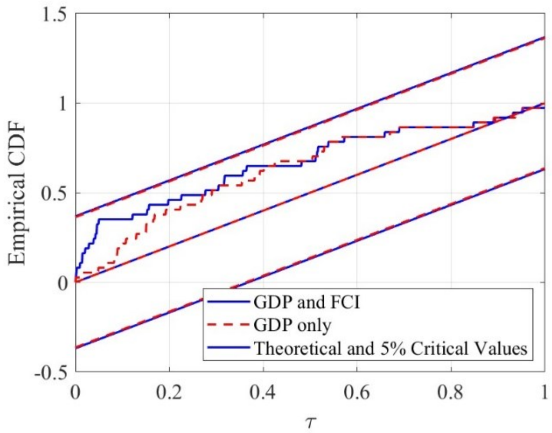
1. US: one year lag model



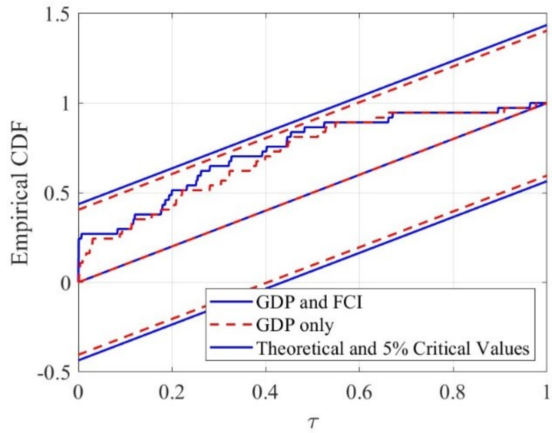
2. Euro Zone: one year lag model



3. Argentina: one year lag model



4. Brazil: one year lag model



5. India: one year lag model