Stock market as a nowcasting indicator for real investment

Degiannakis, Stavros

Panteion University of Social and Political Sciences, Bank of Greece

31 December 2021

Stock market as a nowcasting indicator for real investment

Stavros Degiannakis[1]
Bank of Greece, Economic Research Department, 21 E. Venizelos Avenue, GR10250, Athens, Greece,
Panteion University of Social and Political Sciences, Department of Economics and Regional Development, 136 Syggrou Av., GR17671, Athens, Greece.

Abstract

The paper proposes a novel method to assess whether real investment can be nowcasted based on information that is available on the stock market. The stock market index on a daily sampling frequency is assessed as a predictor of gross fixed capital formation on a quarterly sampling frequency. For France, Germany, Greece and Spain (four representative countries of eurozone), we find significant empirical evidence that the information from the stock market does produce accurate nowcasting values of gross fixed capital formation.

Keywords: Gross fixed capital formation, nowcasting, mixed frequency, predictor, real investment, stock market.

JEL Classifications: E27, C53.

1. Introduction

Traditionally, financial research studied the relationship between finance and growth via the banking system and the traditional intermediation channel; e.g. Gurley and Shaw (1955), Goldsmith (1969) and Keynes (1973). However, over the last three decades, research has revealed the role of the stock markets in economic growth (*i.e.* King and Levine, 1993, Rousseau *et al.*, 1998 and Levine *et al.*, 2000, Morck *et al.*, 1990). Hence, the related literature has studied, in the past, the relationship between economic growth and the financial system (stock markets and banking system) extensively. The focus of these studies was on estimating the causal relationships between stock market and economic growth.

[1] e-mail: s.degiannakis@panteion.gr

The literature did not deliver clear results; there was evidence of causality from the stock market to economic growth, from economic growth to the stock market, bidirectional and even no causality at all. Barro (1990) provided empirical evidence that the stock prices have substantial explanatory power for U.S. aggregate business investment, especially for long-term samples that begin in 1891 or 1921. The positive relationship between investment and stock market prices has been rationalised by the studies of Barro (1990) and Fama (1981) based on the Tobin's (1969) *q* theory[2]. Indicatively, we note that Hondroyiannis *et al.* (2005) estimated a number of vector error correction models in order to assess the relationship between stock market and economic growth for Greece. Marques *et al.* (2013) estimated the relationship between stock market and economic growth for Portugal based on VAR models. Luintel and Khan (1999) examined the long run causality between financial development and economic growth using data from 10 countries. The findings are in line with the endogenous growth literature.

Despite the extensive empirical research on the causal relationship between stock markets and economic growth, the literature has rather neglected to assess whether stock market can indeed offer nowcasting information on economic growth and whether this information can be associated with specific sub-components of *GDP*. Nowadays, from a policy making perspective, the nowcasting of economic growth (not only for the *GDP* but for its components as well) is crucial; see *i.e.* ECB (2008). The motivation to the undertaken research is grounded on the need of economists and policy makers to nowcast *GDP* and its components given the lags in the publication of statistical information on economic developments. Therefore, in order to monitor the economic activity timely we must estimate models that are based on higher frequency data. Hence, the present paper does not aim to investigate the existence of any causal relationship between the stock market and economic growth. The relationship between the stock market and economic growth had been investigated mainly two decades ago. The present study investigates the ability of stock market to provide nowcasting information for economic growth.

[2] Tobin's *q* measure is the ratio of the market's valuation of capital to the long run cost of acquiring new capital, *i.e.* the replacement cost of the share capital.

The aim of this paper is twofold. First, we focus on whether the information that can be extracted from stock markets can be useful in nowcasting exercises and second, we concentrate our research solely on real investment, which is the component of *GDP* that is directly related to stock market developments. We construct a mixed frequency time series model, *i.e.* a *MIDAS* model, in order to estimate the relationship between two variables that are sampled at different frequencies; the daily sampled stock market returns and the quarterly sampled gross fixed capital formation (*GFCF*). To our knowledge, this is the first approach that quantifies the information extracted from stock market on daily frequency when we focus on estimating real investment. The contribution of the paper to the literature is based on the empirical *MIDAS* modelling approach, but the motivation is coming from the aforementioned literature which had showed that stock markets and real investment may be highly related.

Based on a dataset from two core and two periphery countries of the Eurozone; *i.e.* France, Germany, Greece and Spain, we provide strong evidence that the stock market does serve as a nowcasting indicator for gross fixed capital formation. Stock market growth sampled on a daily basis is able to provide accurate nowcasting estimates of *GFCF*. But, only under the correctly defined econometric framework, we can reveal the relationship between the stock market and *GFCF*. A relationship that is highly significant and it appears with a time lag of three months for France, Germany and Spain, and with a 10 month lag for Greece.

In the rest of the paper, Section 2 presents the construction of our mixed data sampling model. Section 3 provides the empirical evidence from France, Germany, Greece and Spain, and Section 4 presents our conclusions.

2. The method: A MIDAS approach

GDP and its components are published on a quarterly basis, but stock market indices are available in real time; *i.e.* the prices are recorded intraday, even every second, depending on the liquidity and the microstructure of each market. However, when we refer to asset prices, we tend to use the daily closing prices. Usually, the relationship between two variables that are sampled at different frequencies is modelled with three techniques. The first approach is to re-sample the variable available at the higher frequency (*i.e.* daily) to the frequency that the second variable is available (*i.e.* quarterly). The second approach is the construction of a regression with as many regressors as the number of intra-points; for example if we want to estimate a monthly regression with daily high frequency regressors, we have to add 22 components as regressors. Usually, this approach requires a large number of coefficients making the estimation of the model infeasible. The third method is to employ a model of mixed frequency sampling (*i.e.* Mixed Data Sampling- *MIDAS*). The advantage of the third method is the flexible parameterization of the response of the high frequency dependent variable to the lower frequency data, based on a polynomial parsimonious parameterization. Henceforth, we proceed to the construction of a *MIDAS* specification, according to Andreou *et al*. (2010 and 2013) for gross fixed capital formation (*GFCF*) imposing some realistic assumptions regarding its asynchronous relationship with stock market:

$$y_q = \beta_0 + \sum_{\tau=0}^{k-1} x_{(d-\tau-is)} \left(\sum_{j=0}^{p} \tau^j \theta_j \right) + \varepsilon_q, \qquad (1)$$

where $y_q = log\left(GFCF_q / GFCF_{q-1}\right)$ is the quarterly log-growth of *GFCF*, $x_{(d)} = log(X_d / X_{d-1})$ is the daily log-return of stock market and $\varepsilon_q \sim N\left(0, \sigma^2_{\varepsilon_q}\right)$ defines the residuals of the model. We do not need to specify the distribution of ε_q, as long as the independency over time holds. But, the assumption of normally distributed errors is required for the definition of the maximum likelihood that is estimated numerically as well as for the statistical inference. The β_0 and θ_j are coefficients to be estimated, p is the order of Almon's polynomial, k is the number of lags for the trading days, and $s = 66$ defines, approximately, the number of trading days within a quarter. The i term, which defines the point in time that information is available, identifies the ability of the model to estimate *real forecasts*. For example, let us set $i = 0$. We are, then, able to estimate the *GFCF* of the running quarter, *i.e.* $y_{q\backslash q}$. Whereas, if we set $i \geq 1$ and $is \geq 66$, then we are able to estimate the *GFCF* for the next quarter, *i.e.* $y_{q+1\backslash q}$, etc. The term *real forecasts* outlines the estimation of a prediction based solely on information published prior to the point in time that we want to forecast. It should be noted, however, that the *look ahead bias* needs to be handled very carefully, as it is observed in many empirical studies.

Based on the realistic assumption that the stock market is a leading indicator of economic growth, we would like to estimate the *MIDAS* framework for the optimum distance between realizations of real investment and stock market. Thus, we wish to define the framework that estimates the *most accurate* nowcast of *GFCF*, given the information revealed from stock market, $x_{(d)}$. Thus, we define the term *most accurate* as the minimum distance between the nowcast of *GFCF* and the actual *GFCF*. Two metrics of statistical distance are widely used; the squared distance and the absolute percentage distance. Thus, the model defined in eq.(1) is estimated by minimising the following loss functions:

$$\min_{(d)}\left(Q^{-1}\sum_{q=1}^{Q}\left(GFCF_q - GFCF_{q\backslash q}\right)^2\right), \quad (2)$$

and

$$\min_{(d)}\left(Q^{-1}\sum_{q=1}^{Q}\frac{\left|GFCF_q - GFCF_{q\backslash q}\right|}{GFCF_q}\right), \quad (3)$$

where $GFCF_q$ is the GFCF of quarter q, $GFCF_{q\backslash q}$ is the estimation of $GFCF_q$ given the $x_{(d)}$ up to trading day *d*, and Q is the number of quarters that the model is being estimated. For each *d*, the $GFCF_{q\backslash q}$ is the conditional estimate based on information available up to quarter *q*. Hence $GFCF_{q\backslash q} \equiv E\left(GFCF_q \backslash I_q\right)$ is being estimated iterated for each point in time $q = \ddot{q}, .., Q$, where $\ddot{q}$ defines the least number of observations that makes the estimate of eq.(1) feasible. Overall, the estimation of the *MIDAS* model for the optimum *d*, requires the estimation of the model for $(Q - \ddot{q})D$ times, for $d = 1, \dots, D$, where D is defined as the upper limit for the unknown d . We have found that D =360 fulfils our requirements.

Therefore, our interest focuses on the estimation of *d*; *i.e.* the exact number of past trading days that the stock market reveals as the most appropriate conditional estimate of actual *GFCF*. We note that the proposed optimization technique is close to that introduced by Bragoudakis *et al.* (2020) for modelling the asymmetric relationship of oil and pump prices. However, the fundamental improvement of the method we propose is the optimization based of the conditional estimates instead of the unconditional ones. For example, if we had followed Bragoudakis *et al.* (2020) method, then, instead of eq.(2), we would have defined the $\min_{(d)}\left(Q^{-1}\sum_{q=1}^{Q}\left(GFCF_q - \widehat{GFCF}_q\right)^2\right)$ where $\widehat{GFCF}_q$ defines the unconditional estimate of *GFCF* for quarter *q* based on the full sample. If that was the case, then the estimation would have been simpler[3].

3. Empirical evidence: The case of France, Germany, Greece and Spain

We estimate the proposed framework for four countries, two core and two periphery countries of the eurozone; *i.e.* France, Germany, Greece and Spain[4]. The gross fixed capital formation in millions of € is available from 2000q1 up to 2020q3 from the Federal Reserve Bank of St. Louis (in the case of Greece, the data are available from 2002q1 and were collected from the Hellenic Statistical Authority). For the same period, but on a daily basis, the Cotation Assistée en Continu - *CAC40* (France), the Deutscher Aktien Index - *DAX30* (Germany), the Athens Stock Exchange General Index – *ASEGI* (Greece) and the Índice Bursátil Español - *IBEX35* (Spain) have been considered as representative indices of the stock market.

Let us review some descriptive characteristics of *GFCF* and stock market indices. Table 1 presents the descriptive statistics of gross fixed capital formation and its *q-o-q* growth in logs. The differences between the four countries are more than profound. According to Figure 1, France depicts a stable *GFCF/GDP* ratio over time. Germany has an up trending contribution of investments on *GDP*. On the other hand, both Greece and Spain present a decreasing *GFCF/GDP* ratio from 2007 to the present. In 2007 Greece reached a 27% contribution of *GFCF* to *GDP*, but over the last two years it ranges from 11% up to 12%. In the case of Spain, the ratio was at the highest level, around 30%, in 2006-2007 and it dropped to 20% in 2020.[5] Table 2 presents the descriptive statistics of stock market indices and their daily log-returns. All the markets have qualitatively similar characteristics that have been mentioned in financial literature repeatedly; they are negatively skewed with high kurtosis and excess volatility. We also observe that on a daily frequency, the log-returns range from around -15% to +13%.

[3] In order to realize the difference between the two techniques, we notice that the optimization based on the conditional estimates requires 6 hours computational time (on a i7-7700HQ CPU @ 2.80GHz), whereas the optimization based on the unconditional estimates requires 5 minutes.
[4] France, Germany, Greece and Spain have been selected as major representatives from the groups of core and periphery eurozone countries.
[5] The figures are qualitatively similar for both nominal and real values.

[Insert Figure 1 about here]

[Insert Tables 1&2 about here]

Figure 2 provides visual evidence that the stock market has a common trend with *GFCF*, although not identical. For all these countries there are periods in which the two indices deviate. At first sight we understand that there is a common course which is also influenced by other factors. Thus, we can not extract the exact relationship between the stock market and investments without using an advanced econometric method.

[Insert Figure 2 about here]

So, based on the *MIDAS* specification, we estimate the time lag which better describes the non-linear relationship between the stock market of past trading days and nowcasted *GFCF*. The estimation of eq.(1), given the minimisation of either eq.(2) or eq.(3), provides similar results. Thus, in Figure 3, we present a smoothed average of the standardized values of the eq.(2) and eq.(3) loss functions (the details are available in Appendix 1). According to Figure 3, the index displays minimum values in the time window of three months for all the countries other than Greece. Specifically, d equals 74, 71, 216 and 74 trading days for France, Germany, Greece and Spain, respectively. So, the meaning of the estimated d is that the growth rate of the stock market serves as a nowcasting indicator of *GFCF* a quarter ahead, except for the case of Greece, where the stock market serves as a nowcasting indicator of *GFCF* after a period of 10 months (or 216 trading days).

[Insert Figure 3 about here]

Figure 4 presents the relationship between actual *GFCF* and estimated *GFCF* according to the proposed model specification. The nowcast values of *GFCF* based on the *MIDAS* model are quite accurate. In panel A of Table 3, the root mean squared nowcast error (*RMSE*) and the mean absolute nowcast error (*MAPE*) are presented. For France and Germany the mean percentage error is about 1%, for Spain 1.8% and for Greece 5.64%. Of course, we must have a benchmark. As a benchmark, we can define the performance of a simpler model. Let us assume that we had not defined the *MIDAS* model and we were not aware of the minimization of the eq.(2) and eq.(3) loss functions. The naïve model that we could estimate is the regression of the stock market on a quarterly frequency on *GFCF*.[6] Of course, under a simple regression model, we are not able to estimate the *d* value that best describes the relationship between stock market growth and real investment. Thus, we have to estimate the simple regression under the hypothesis that we do know the estimate of *d*. Even under this assumption, the naïve model is not able to replicate the estimated accuracy of the proposed *MIDAS* specification.

[Insert Figure 4 about here]

[Insert Table 3 about here]

Figure 5 provides scatterplots of actual *GFCF* and estimated *GFCF* based on the naïve regression model. Additionally, panel B of Table 3 presents the *RMSE* and *MAPE* values of the naïve regression model. Comparing the loss function values we can see the significant gains from the use of the stock market information on a daily frequency. We have applied the model confidence set of Hansen *et al.* (2011) to test whether the two model specifications have equal predictive accuracy. Under both *RMSE* and *MAPE* evaluation measures, the hypothesis of equal predictive accuracy has been rejected at any rational level of significance. Therefore, the stock market does serve as a nowcasting indicator for real investment. The relationship between stock and *GFCF* is highly significant and it appears with a time lag of three months for France, Germany and Spain, and with a 10 month lag for Greece.

[Insert Figure 5 about here]

4. Conclusion and future research

Empirical evidence, from two core and two periphery countries of the eurozone (France, Germany, Greece and Spain), highlights that stock markets do serve as a nowcasting indicator for real investment. Based on a mixed frequency sampling model, we can reveal the relationship between the stock market and *GFCF*. The information extracted from capital markets on a daily sampling frequency is vital for the nowcasting of gross fixed capital formation.

The delay in the publication of *GDP* forces economists to predict *GDP* and its components even for the current or the previous quarter. For example, the flash estimate of *GDP* for the last quarter

[6] A comparison against a naïve model that does not incorporate information from stock market at all, *i.e.* an autoregressive model, also provides similar findings; the information extracted from stock market is crucial.

of 2021 will be published in mid-February 2022. But, based on higher frequency indicators, we are able to provide nowcasts of *GDP* before the publication date. In the present study, the higher frequency indicators are the stock market prices, which helped in estimating the *GFCF*; *i.e.* the component of *GDP*, before its publication date. The nowcasting is an essential tool of economists and policy makers in order to understand the ongoing economic developments and provide policy makers with vital forward looking information for assessing the unemployment and inflation trends.

The present paper is a preliminary approach to the relationship between capital market growth and real investment. The robustness of the *MIDAS* model can be examined further, under different scenarios and control variables from both an economic and a financial perspective. Of course, in future research, we must analyse the investments by category, e.g. real estate investments, public investments, public and private partnerships, large-scale strategic investments, etc.

Acknowledgements

I would like to thank Helga Stefansson, George Filis and Zacharias Bragoudakis for their useful comments. The views expressed in this paper are those of the author and not necessarily those of either the Bank of Greece or the euro system.

References

Andreou, E., Ghysels, E. & Kourtellos, A. (2010). Regression models with mixed sampling frequencies. *Journal of Econometrics*, 158(2), 246-261.

Andreou, E., Ghysels, E. & Kourtellos, A. (2013). Should macroeconomic forecasters use daily financial data and how? *Journal of Business and Economic Statistics*, 31(2), 240-251.

Barro, R. J. (1990). The stock market and investment. *Review of Financial Studies*, 3(1), 115-131.

Bragoudakis, Z., Degiannakis, S. & Filis, G. (2020). Oil and pump prices: Testing their asymmetric relationship in a robust way. *Energy Economics*, 104755.

ECB (2008). Short-term forecasts of economic activity in the euro area, in Monthly Bulletin, April, 69–74. European Central Bank.

Fama, E.F. (1981). Stock returns, real activity, inflation, and money. *American Economic Review*, 71(4), 545-565.

Goldsmith, R.W. (1969). Financial Structure and Development. Yale University Press, New Haven.

Gurley, J. & Shaw, E. (1955). Financial aspects of economic development. *American Economic Review*, 45(4), 515–538.

Hansen, P. R., Lunde, A. & Nason, J.M. (2011). The model confidence set. *Econometrica*, 79(2), 453-497.

Hodrick, R.J. & Prescott, E.C. (1997). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money Credit and Banking*, 29(1), 1–16.

Hondroyiannis, G., Lolos, S. & Papapetrou, E. (2005). Financial markets and economic growth in Greece, 1986–1999. *Journal of International Financial Markets, Institutions and Money*, 15(2), 173-188.

Keynes, J.M. (1973). The General Theory of Employment, Interest and Money. MacMillan, London, Original Edition: 1936.

King, R.G. & Levine, R. (1993). Finance and growth: Schumpeter might be right. *Quarterly Journal of Economics*, 108, 717–738.

Levine, R., Norman, L. & Thorsten, B. (2000). Financial intermediation and growth: causality and causes. *Journal of Monetary Economics*, 46, 31–77.

Luintel, K.B. & Khan, M. (1999). A quantitative reassessment of the finance–growth nexus: evidence from a multivariate VAR. *Journal of Development Economics*, 60(2), 381-405.

Marques, L.M., Fuinhas, J. A. & Marques, A.C. (2013). Does the stock market cause economic growth? Portuguese evidence of economic regime change. *Economic Modelling*, 32, 316-324.

Morck, R., Shleifer, A., Vishny, R. W., Shapiro, M., & Poterba, J. M. (1990). The stock market and investment: is the market a sideshow? *Brookings Papers on Economic Activity*, *1990*(2), 157-215.

Rousseau, P.L. & Wachtel, P. (1998). Financial intermediation and economic performance: historical evidence from five industrialized countries. *Journal of Money Credit and Banking*, 30, 657–678.

Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of Money, Credit and Banking*, 1(1), 15-29.

Appendix 1

Let us define $\alpha_q = \left(GFCF_q - GFCF_{q\setminus q}\right)^2$ and $\beta_q = \frac{\left|GFCF_q - GFCF_{q\setminus q}\right|}{GFCF_q}$. The estimated mean and variance of α_q are $\bar{\alpha}_q$ and $V\left(\alpha_q\right)$, respectively. Moreover, for β_q, the mean and variance estimators are $\bar{\beta}_q$ και $V\left(\beta_q\right)$, respectively. The standardized loss functions are defined as:

$$\alpha_q^* = \left(\alpha_q - \bar{\alpha}_q\right) / \sqrt{V\left(\alpha_q\right)}, \tag{A1}$$

and

$$\beta_q^* = \left(\beta_q - \bar{\beta}_q\right) / \sqrt{V\left(\beta_q\right)}. \tag{A2}$$

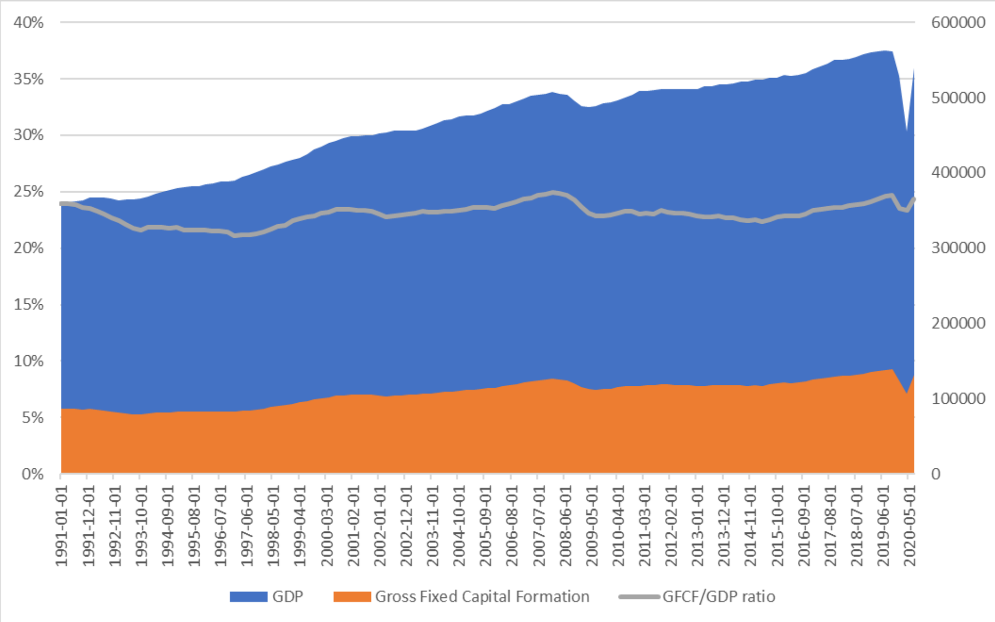
Hence, the index presented in Figure 3 is computed as:

$$I_q^* = f\left(\left(\alpha_q^* + \beta_q^*\right)/2\right), \tag{A3}$$

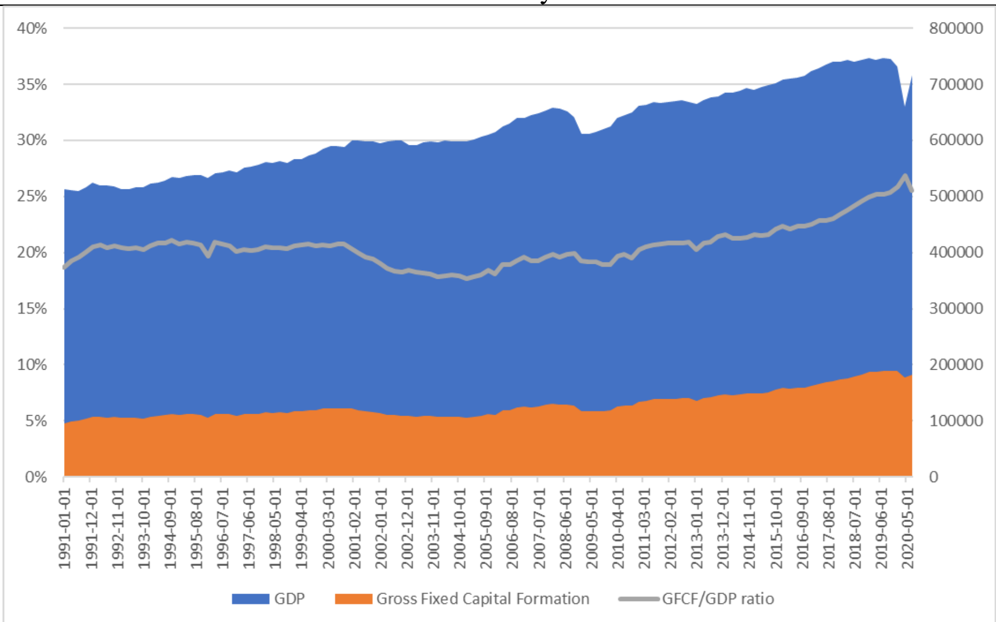
where $f(.)$ is the Hodrick and Prescott (1997) filter.

Figure 1. *GDP* and gross fixed capital formation

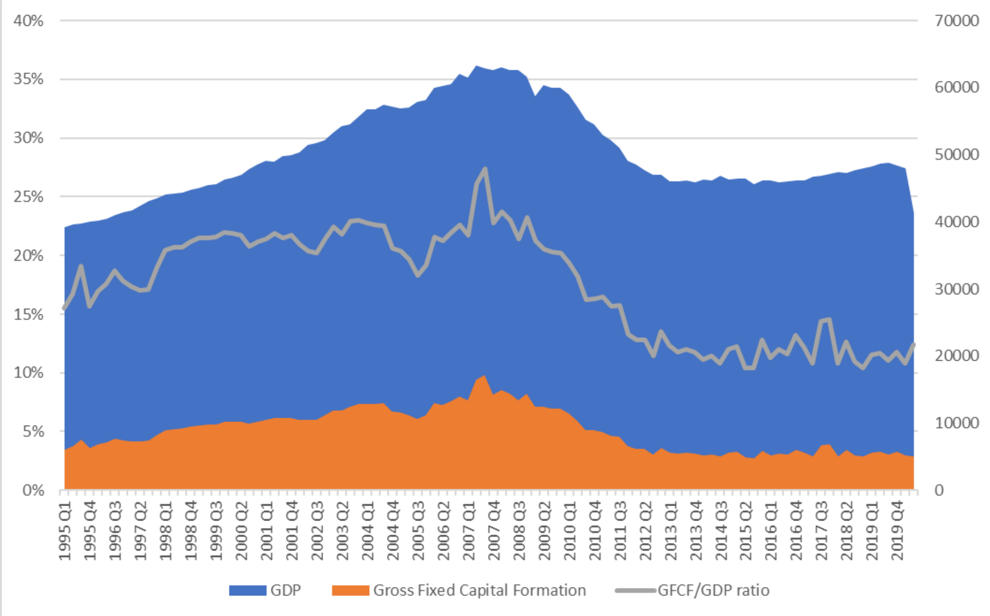
France



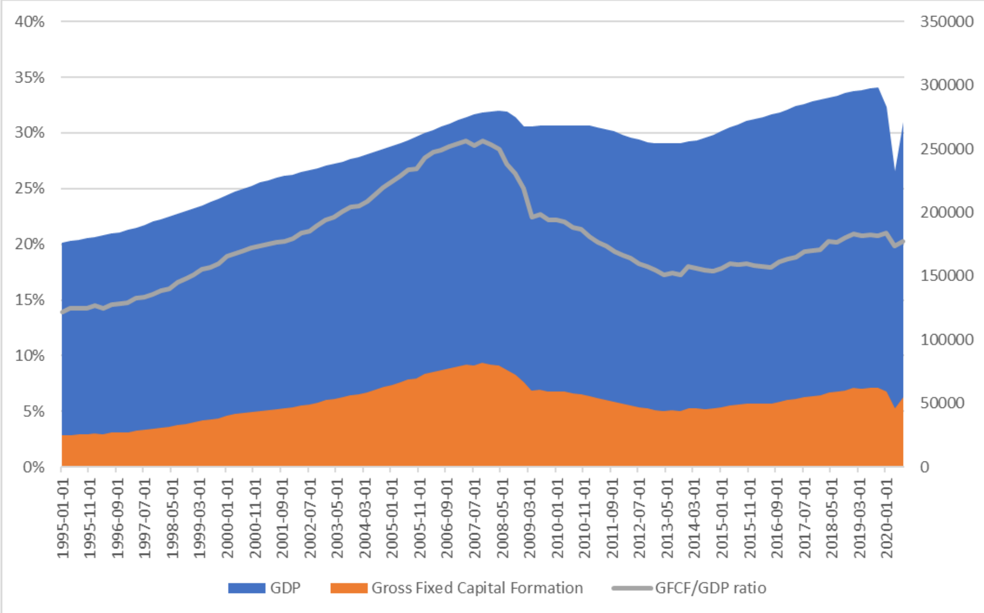
Germany



Greece

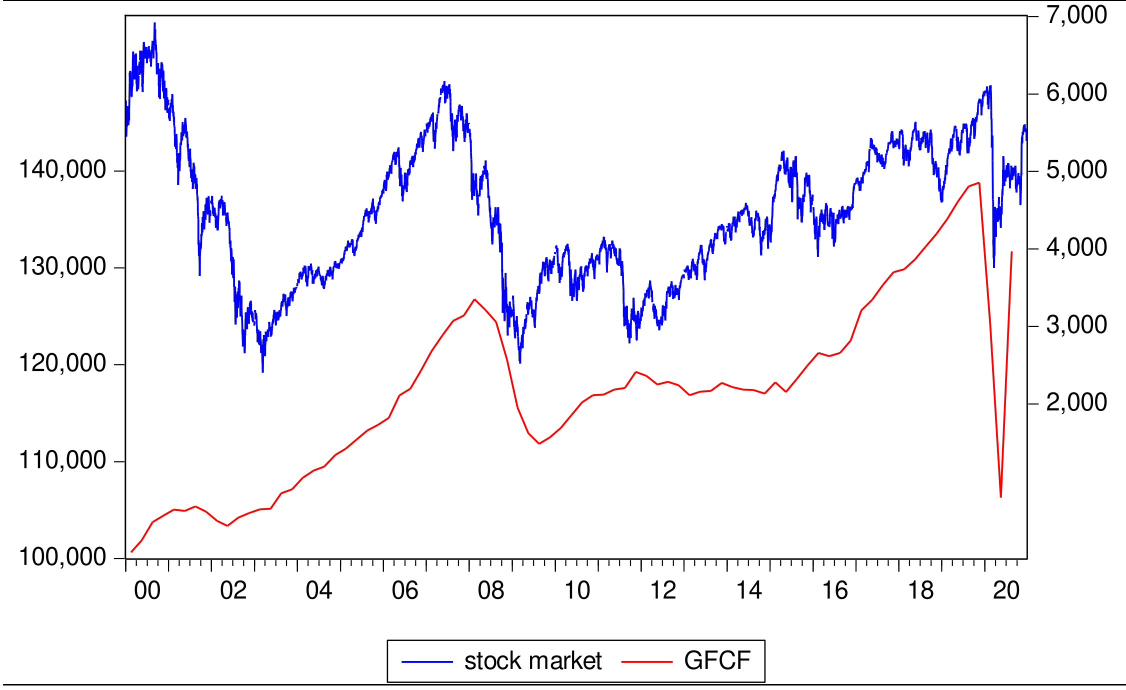


Spain

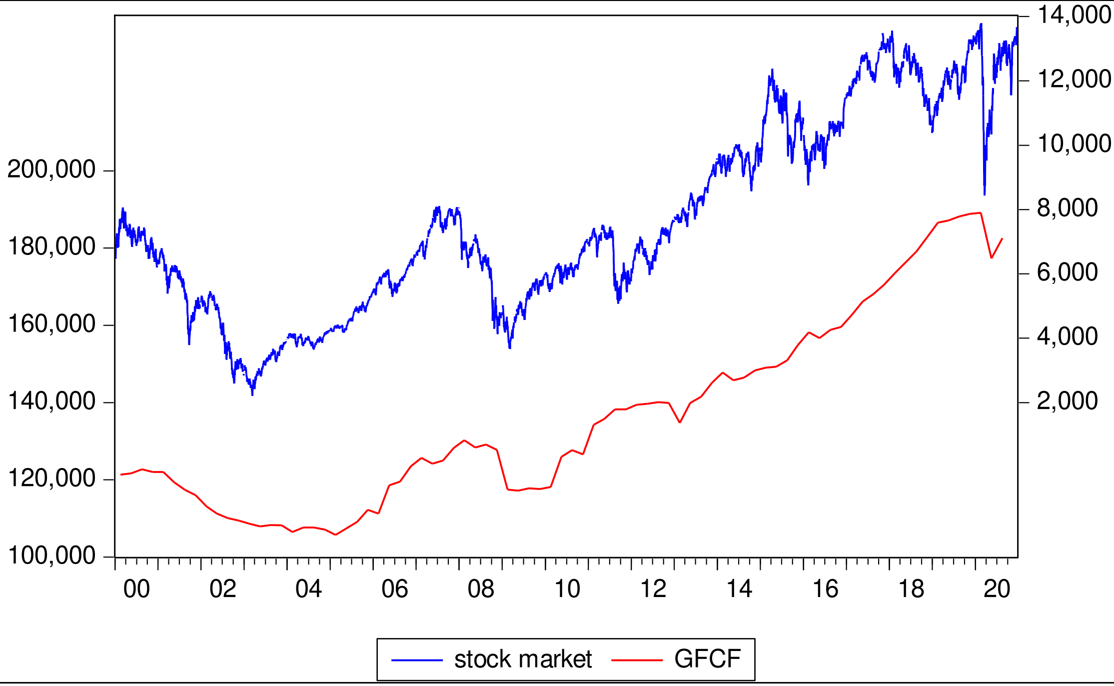


Real values (base year 2010), in millions of €, seasonally adjusted. *GDP* and gross fixed capital formation (*GFCF*) are presented on the right hand side, whereas the ratio *GFCF*/ *GDP* is presented on the left hand side.

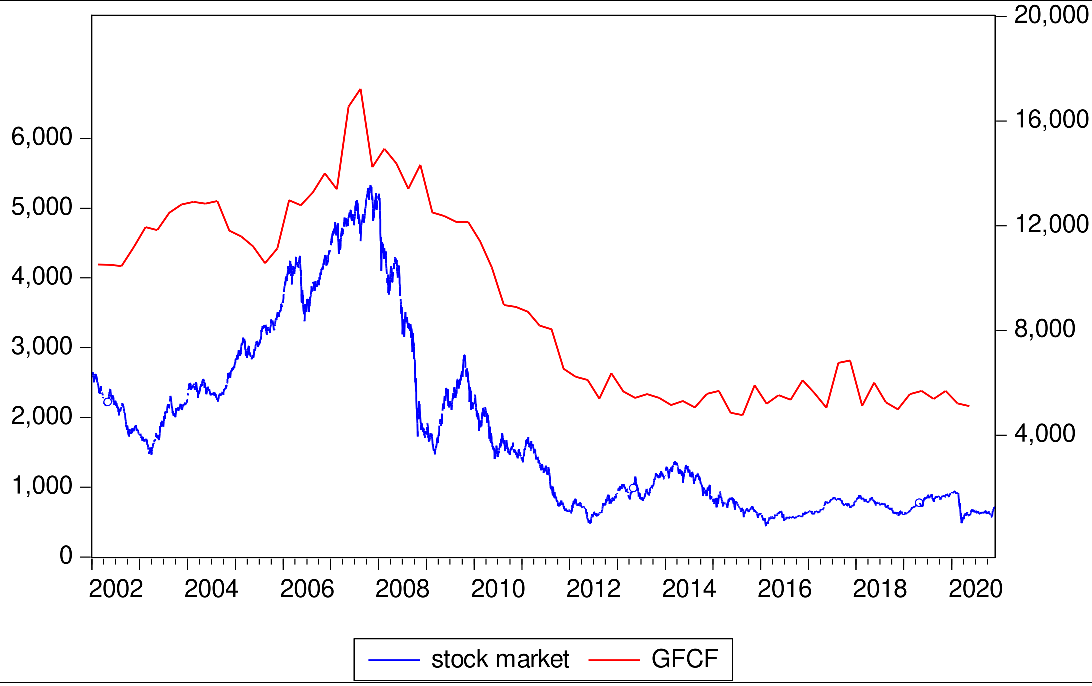
Figure 2. Stock market and gross fixed capital formation



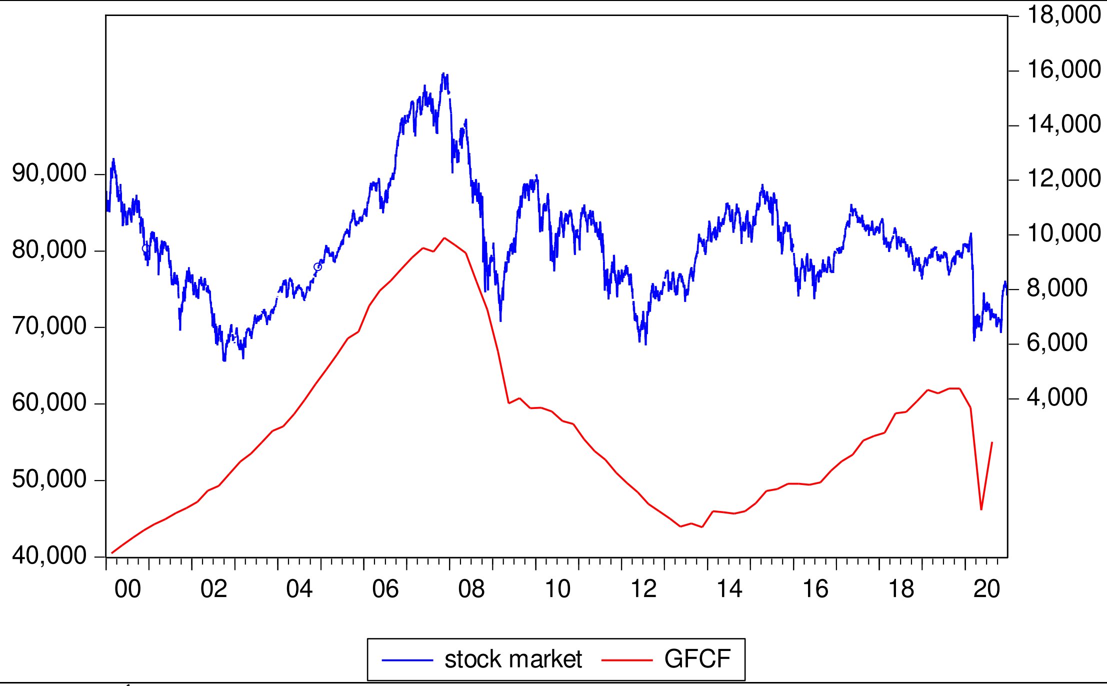
CAC40: Cotation Assistée en Continu (right hand side).
GFCF: Gross Fixed Capital Formation, in real prices, millions of €, seasonal adjusted (left hand side).



DAX30: Deutscher Aktien Index (right hand side).
GFCF: Gross Fixed Capital Formation, in real prices, millions of €, seasonally adjusted (left hand side).



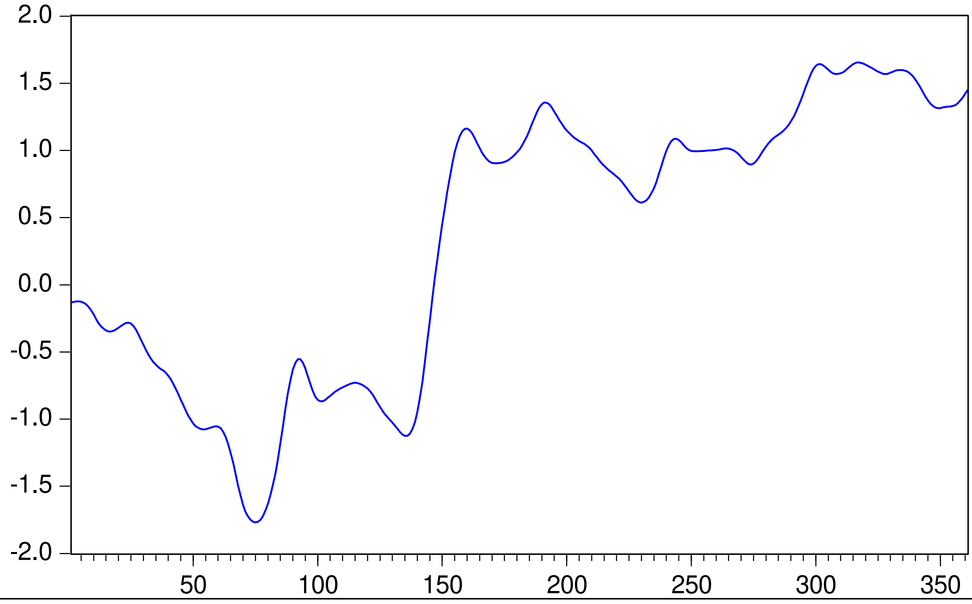
ASEGI: Athens Stock Exchange General Index (right hand side).
GFCF: Gross Fixed Capital Formation, in real prices, millions of €, seasonally adjusted (left hand side).



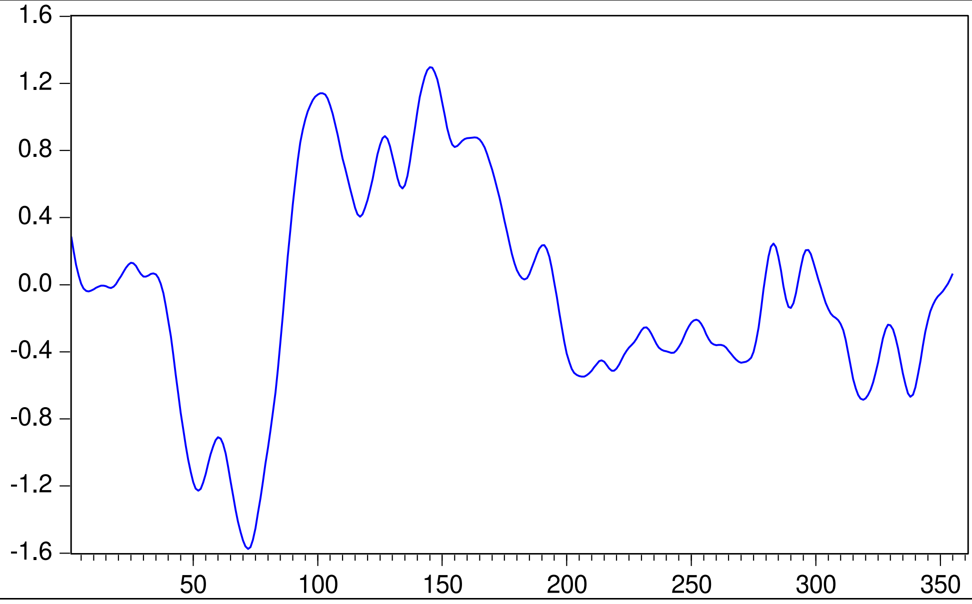
IBEX35: Índice Bursátil Español (right hand side).
GFCF: Gross Fixed Capital Formation, in real prices, millions of €, seasonally adjusted (left hand side).

Figure 3. Smoothed average of the loss functions' standardized values.

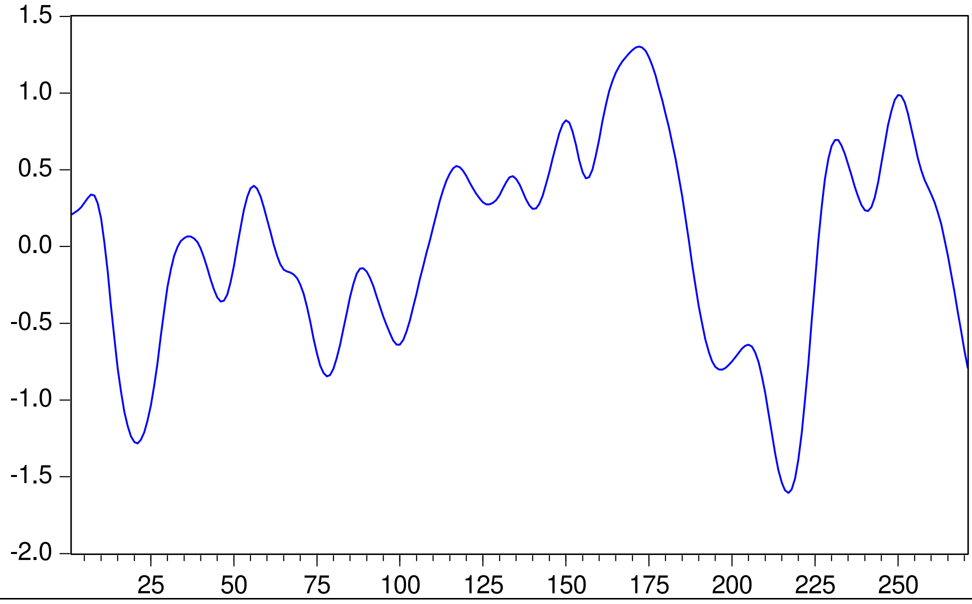
France



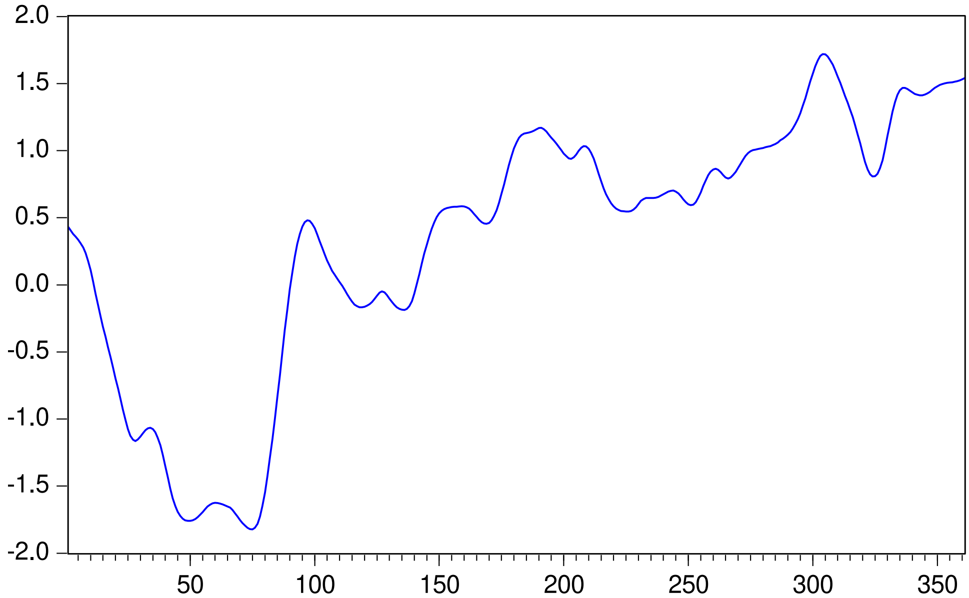
Germany



Greece



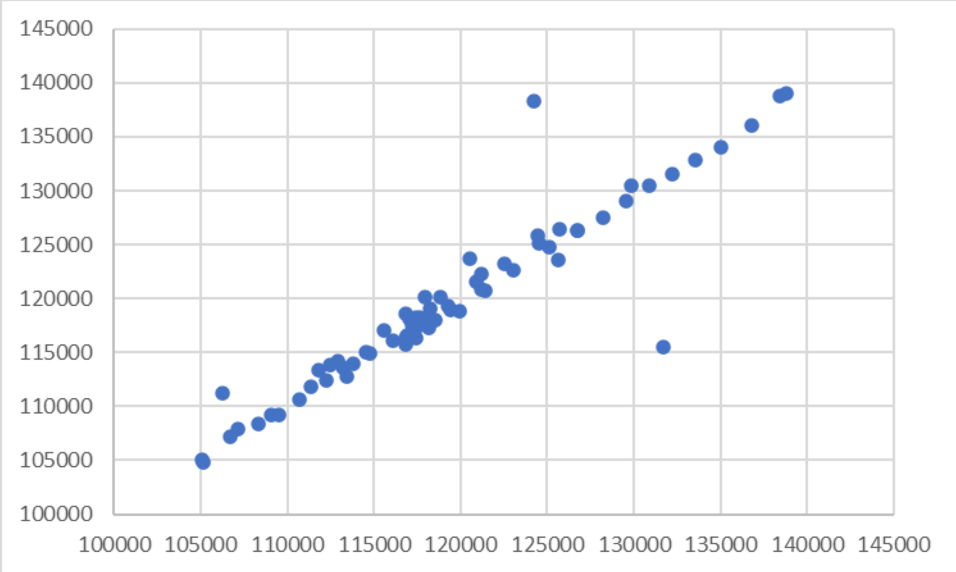
Spain



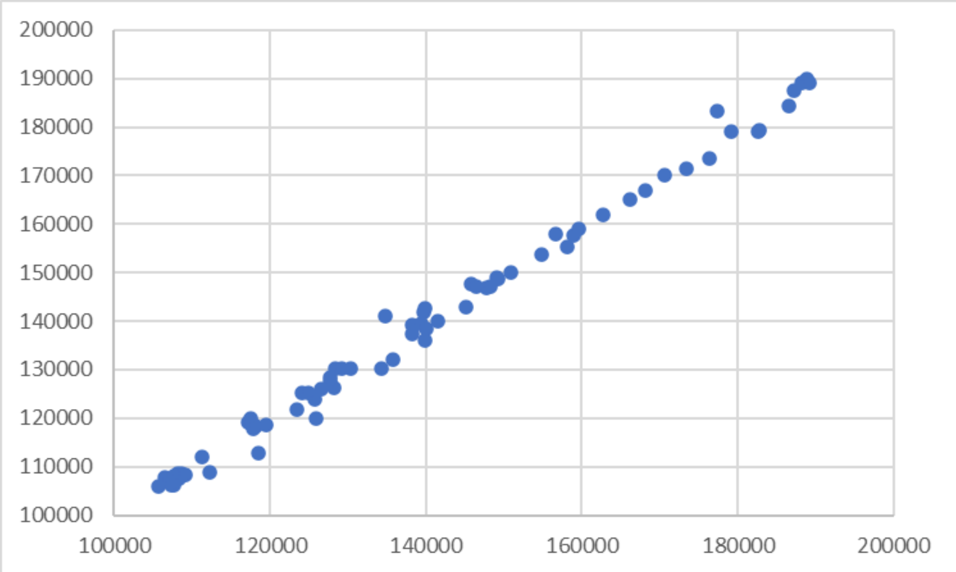
The index values are plotted on the y-axis. The number of trading days is plotted on the x-axis. Figure presents the smoothed average of the standardized values of $\min\limits_{(d)}\left(Q^{-1}\sum_{q=1}^{Q}\left(GFCF_q - GFCF_{q\backslash q}\right)^2\right)$ and $\min\limits_{(d)}\left(Q^{-1}\sum_{q=1}^{Q}\frac{|GFCF_q - GFCF_{q\backslash q}|}{GFCF_q}\right)$, where $GFCF_q$ is the $GFCF$ of quarter q, $GFCF_{q\backslash q}$ is the estimation of $GFCF_q$ given the $x_{(d)}$ up to trading day d, and Q is the number of quarters that the model is being estimated iterated. The construction of the index is presented in Appendix 1.

Figure 4. The actual and *MIDAS* estimated values of gross fixed capital formation.

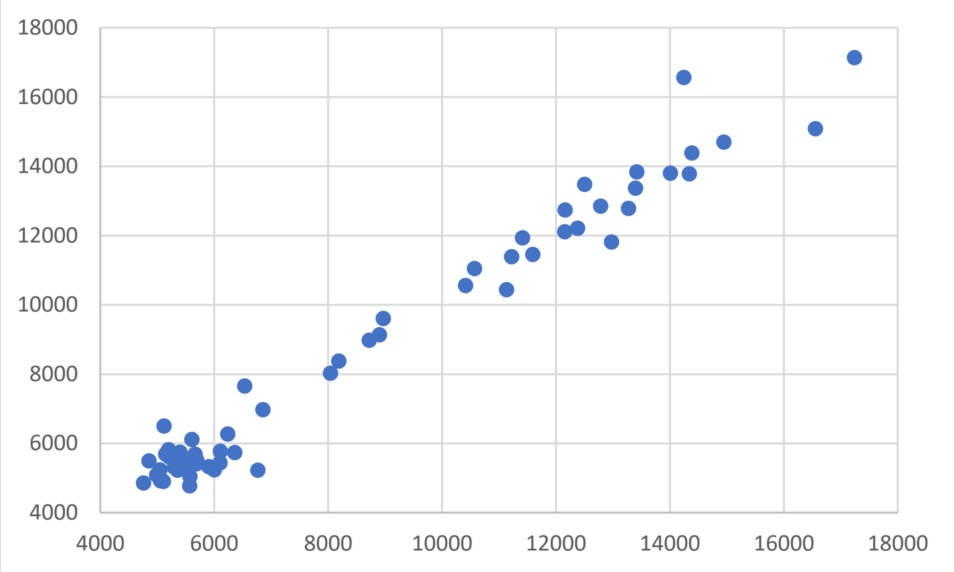
France



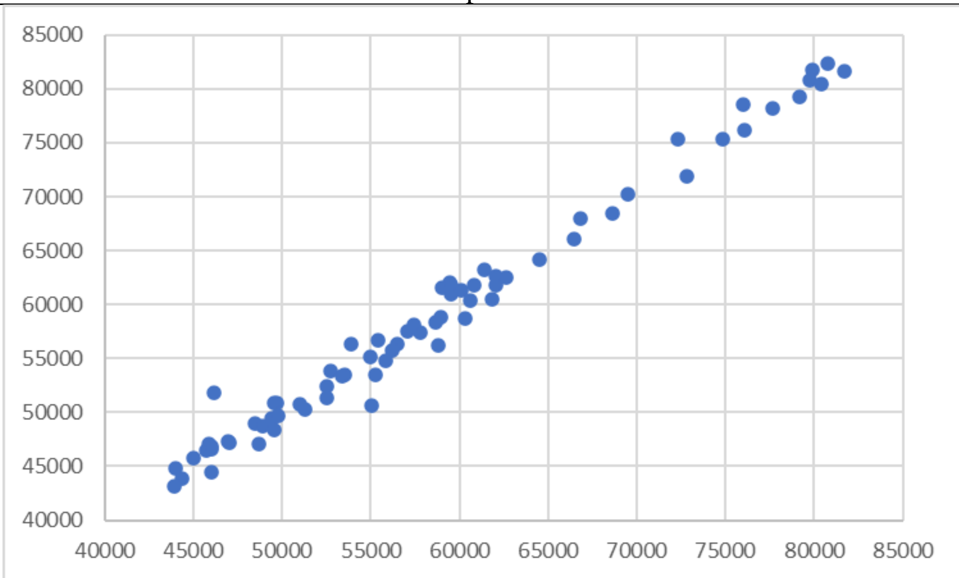
Germany



Greece



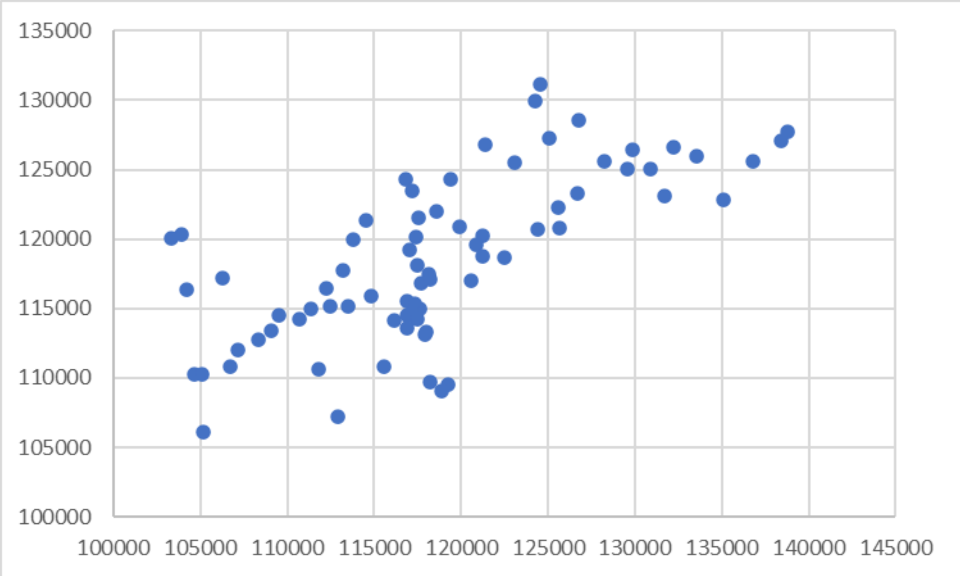
Spain



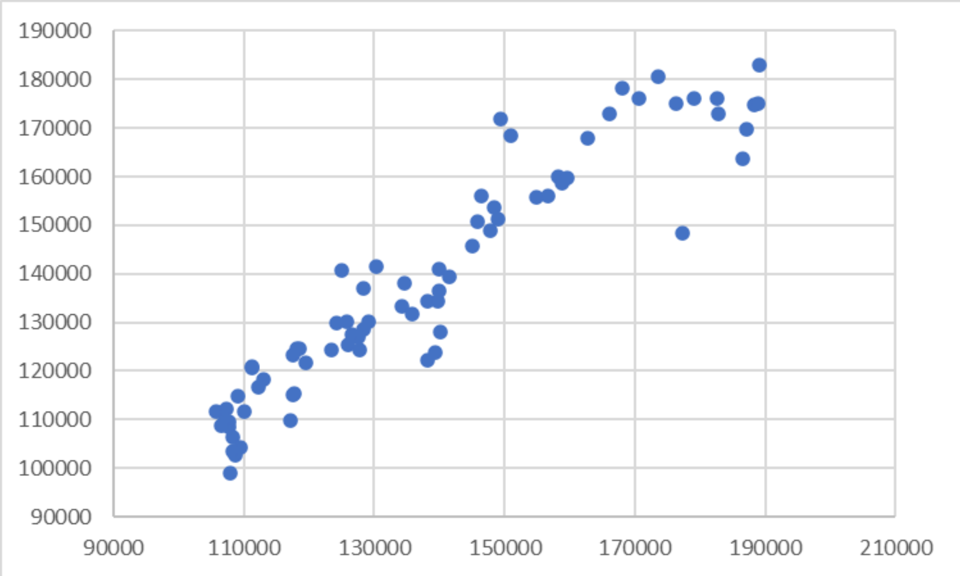
The scatterplots present the relationship between actual and estimated *GFCF*. *GFCF* is plotted on the x-axis. The nowcast values of *GFCF* based on the *MIDAS* model are plotted on the y-axis.

Figure 5. The actual and naïve estimated values of gross fixed capital formation.

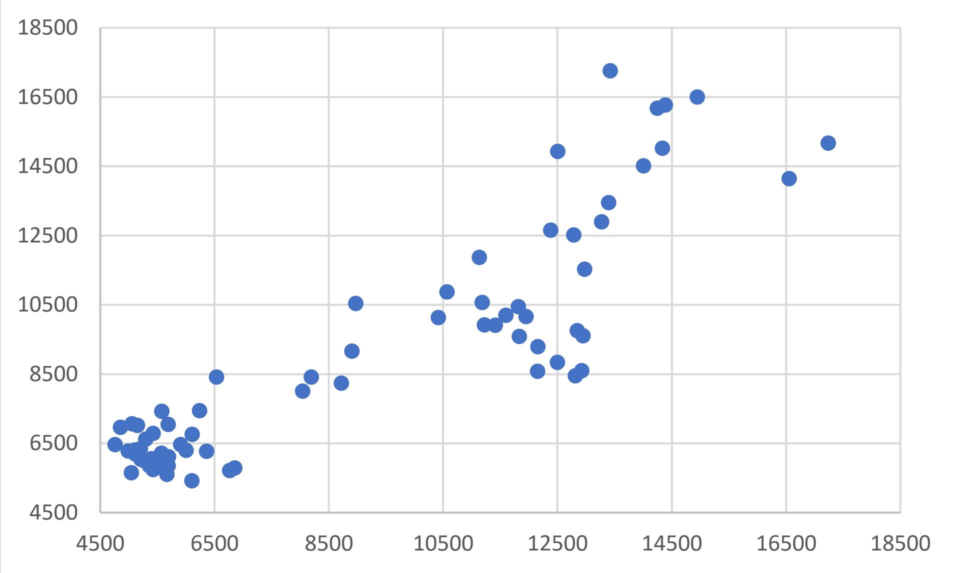
France



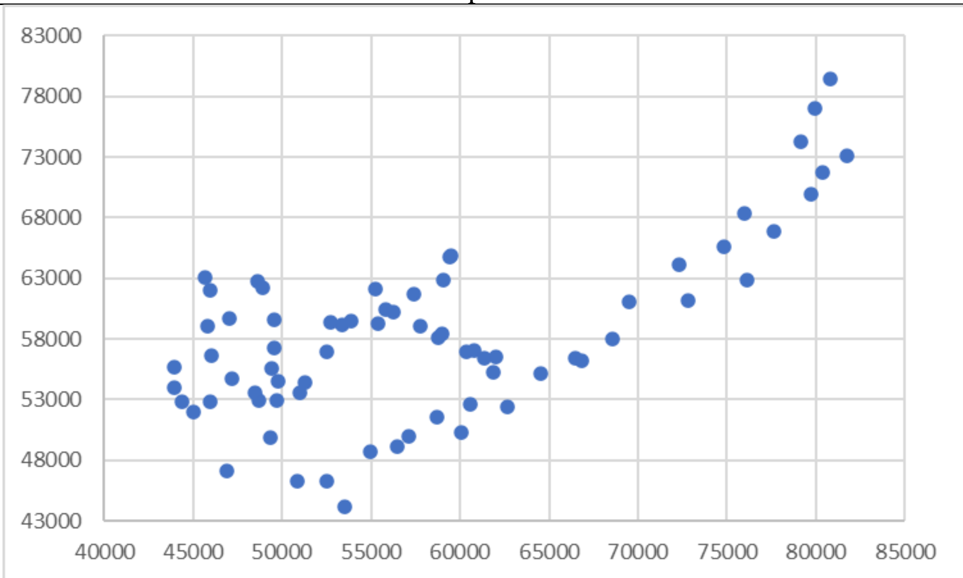
Germany



Greece



Spain



The scatterplots present the relationship between actual *GFCF* and estimated *GFCF* based on the naïve regression model. *GFCF* is plotted on the x-axis. The nowcast values of *GFCF* are plotted on the y-axis.

Table 1. Descriptive statistics of gross fixed capital formation and its *q-o-q* growth (in logs)

	France	Germany	Greece	Spain
	Gross fixed capital formation, in real prices, millions of €, seasonal adjusted			
	France	Germany	Greece	Spain
Mean	117156.6	136556.9	9021.559	56644.65
Median	117393.0	128379.0	8452.563	55042.00
Maximum	138806.0	189119.0	17237.21	81720.00
Minimum	100620.0	105731.0	4756.642	40477.00
Std. Dev.	9137.486	24639.16	3617.798	10985.12
Skewness	0.301537	0.698383	0.339311	0.776007
Kurtosis	2.618335	2.379816	1.691419	2.688945
Observations	83	83	74	83
	q-o-q growth of gross fixed capital formation			
	France	Germany	Greece	Spain
Mean	0.003284	0.004983	-0.009908	0.003748
Median	0.005973	0.004748	-0.018138	0.012294
Maximum	0.214402	0.064023	0.293072	0.176741
Minimum	-0.156146	-0.083792	-0.292144	-0.254991
Std. Dev.	0.033631	0.021738	0.098505	0.044104
Skewness	1.222445	-0.640473	0.286338	-2.053120
Kurtosis	27.43685	7.157049	4.174830	18.57285
Observations	82	82	73	82

Table 2. Descriptive statistics of stock market indices and their daily log-returns

	Stock Market Index			
	France *CAC40*	Germany *DAX30*	Greece *ASEGI*	Spain *IBEX35*
Mean	4467.871	7658.030	1801.626	9682.110
Median	4432.135	6970.760	1323.360	9521.900
Maximum	6922.330	13789.00	5334.500	15945.70
Minimum	2403.040	2202.960	440.8800	5364.500
Std. Dev.	918.7882	3004.136	1272.556	2017.515
Skewness	0.155641	0.384836	1.053646	0.665873
Kurtosis	2.209042	1.978498	3.061343	3.564193
Observations	5360	5324	4711	5330
	Log-returns of the stock market index			
	France *CAC40*	Germany *DAX30*	Greece *ASEGI*	Spain *IBEX35*
Mean	-1.27E-05	0.000131	-0.000275	-6.82E-05
Median	0.000341	0.000760	0.000295	0.000555
Maximum	0.105946	0.107975	0.134311	0.134836
Minimum	-0.130983	-0.130549	-0.144131	-0.151512
Std. Dev.	0.014466	0.014924	0.018543	0.014813
Skewness	-0.200686	-0.170485	-0.317340	-0.277037
Kurtosis	9.306631	8.742528	9.697338	10.80938
Observations	5359	5323	4710	5329

Table 3. The *RMSE* and *MAPE* loss function for the nowcast values of *GFCF* based on the mixed frequency model (panel A) as well as on the regression model (panel B).

Panel A	Mixed frequency model (*MIDAS*)			
	France	Germany	Greece	Spain
RMSE	2746	2153	612	1453
MAPE	0.95%	1.12%	5.64%	1.80%
Panel B	Regression model			
	France	Germany	Greece	Spain
RMSE	5993	8490	1669	7881
MAPE	4.12%	4.35%	14.96%	12.39%