

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/354753843>

# Time-varying Granger causality between the stock market and unemployment in the United States

Preprint · September 2021

CITATIONS

0

READS

555

1 author:



Vincent Fromentin

University of Lorraine

44 PUBLICATIONS 483 CITATIONS

SEE PROFILE

Vincent FROMENTIN

Université de Lorraine – CEREFIGE - DEM

[vfromentin@gmail.com](mailto:vfromentin@gmail.com)

**Keywords:**

Stock market

Unemployment

Time-varying causality

United States

**JEL Codes:**

C32

E44

G14

J60

**ABSTRACT**

In this paper, we look at the connection between the stock market and the unemployment rate in the United States. Using a recent time-varying Granger causality framework covering the period from January 1960 to October 2020, tests reveal that lagged realizations of the stock market have predictive power regarding unemployment, and vice et versa, but that the predictive ability only occurs sporadically over time, particularly during “crash” periods. These results are in line with the literature on the information spillover between finance markets and the real-life economy, with changes of causality across time.

## 1. Introduction

The 2007-2008 financial crisis highlighted the connection between the financial and labor markets for policy makers, economists, business practitioners and academics. Several studies show that the stock market can affect the real-life economy, and notably unemployment<sup>1</sup>. The stock market can be an indicator of how economic activity will act in the future, and increased stock market returns can point to a future drop in the unemployment rate (Fromentin and Tadjeddine, 2020). For example, the work of Phelps (1994), Hoon and Phelps (1992) and Phelps and Zoega (2001) makes a link between the stock market and unemployment rates through arguments based on the expected profits and the impact on employment.

The premise that stock markets will necessarily bring down unemployment when they are more active could be based on several transmission channels, of which Feldmann (2011) presents four (e.g. see Fromentin, 2021). First, because stock markets foster investment in long projects, they stimulate both global saving and investment, thus allowing for economies of scale and scope. As a result, resource allocation becomes easier, including the allocation of labor. Second, stock markets provide funds for business creation – partly directly, through initial public offerings, and partly indirectly, by spurring the growth of venture capital – which motivates job creation in all sectors. Third, stock markets are useful for pinpointing promising investment opportunities and then supplying them with funds. This financial activity boosts both the allocation of resources and economic development, which has the effect of bringing down unemployment. Fourth, liquid stock markets provide a way of monitoring companies after providing finance, and supply relevant information. As a result, labor is efficiently allocated and savings are more likely to be redirected towards investment and innovation.

The debate about the interrelations between stock-market and unemployment fluctuations, studied in several papers by Farmer (2012, 2013, 2015), has expanded with several theoretical or empirical studies. Farmer comes to several conclusions, one of which is that the absence of relevant price signals can have the effect of trapping a market economy in an equilibrium with a high unemployment rate. In addition, unlike the new-Keynesian version of the General Theory, the explanation for a recession does not presume that prices are sticky. The author employs US data to argue that household beliefs regarding US stock market wealth were behind the move from a high-employment equilibrium to a low-employment equilibrium, and that the 2008 market crash constitutes a credible causal relationship for the Great Recession. In brief, he describes the part played by animal spirits and applies different econometric methodologies (Granger causality, cointegrated vector, VECM, etc.) to argue that unemployment was in fact caused by the stock market.

Reciprocally, the stock market can respond to unemployment<sup>2</sup>. Stock prices are impacted by news on unemployment rates because of the information it contains about one or more of the primitives (Boyd *et al.*, 2005), through the information about future interest rates that is contained in the unemployment news. Unemployment news can feature information on growth expectations and/or the equity risk premium in the current business cycle phase. Boyd *et al.* (2005) show that news of an increase in unemployment has positive consequences on stocks during economic growth periods, and negative effects at times of economic decline. Likewise, Chen (2009) shows that unemployment rates

---

<sup>1</sup> Some studies examine whether and how the search intensity data obtained from Google Trends contributes to nowcasting of the U.S. unemployment rate compared to the conventional AR model (like Nagao *et al.* (2019)).

<sup>2</sup> Pan (2018) proposes a brief review of the literature.

can be a good stock market predictor in the short term, but much less so after one year. Applying a vector autoregressive model with time-varying parameters, Christou *et al.* (2020) find that a positive uncertainty shock results in an increase in the unemployment rate.

Fritsche and Pierdzioch (2017) employ German data to constitute empirical evidence for Farmer's view. Their model features a search friction in the labor market and a macroeconomic "belief function" (the log ratio of asset prices to money wages). The latter establishes steady-state employment/unemployment levels based on causality. Employing a VECM representation to test for long-run and short-run Granger non-causality, as well as Granger non-causality in the frequency domain, these authors show that a macroeconomic "belief function" causes fluctuations in the unemployment rate. Pan (2018) uses panel data to show that Farmer's model provides a possible explanation for what occurs in advanced countries, and especially the G7, but that it cannot explain what occurs in developing and emerging countries. Sibande et al. (2019) analyze the causal relationship between stock market returns and unemployment in the UK. The authors demonstrate that the United Kingdom's fluctuating growth and decline, which has historically driven the country's business cycle, is central to the spillover of information that takes place between the stock market and the labor market.

Drawing on existing literature, this article aims to answer the following questions: is there a unidirectional or bidirectional causality between stock market returns and unemployment? If so, does it concern specific periods in the United States?

To answer these questions, and to contribute to the existing literature, we implemented a Granger causality test robust to the presence of instabilities (Rossi and Wang, 2019) using monthly data from 1960m1 to 2020m10 in the United States. This study extends previous analyses by resorting to a recent methodology, which makes it possible to take into account the significance of the causal relation over time while mastering the problem of the stationarity of the data over a very long period. In addition, we show the interest of this research for policy makers, economists, business practitioners and academics, considering the conclusions of the theoretical model and the empirical results.

The remainder of the paper is organized as follows: Section 2 discusses the data, while Section 3 provides a brief outline of the Granger causality test robust to the presence of instabilities and Section 4 present the results, with Section 5 concluding the paper.

## 2. Data

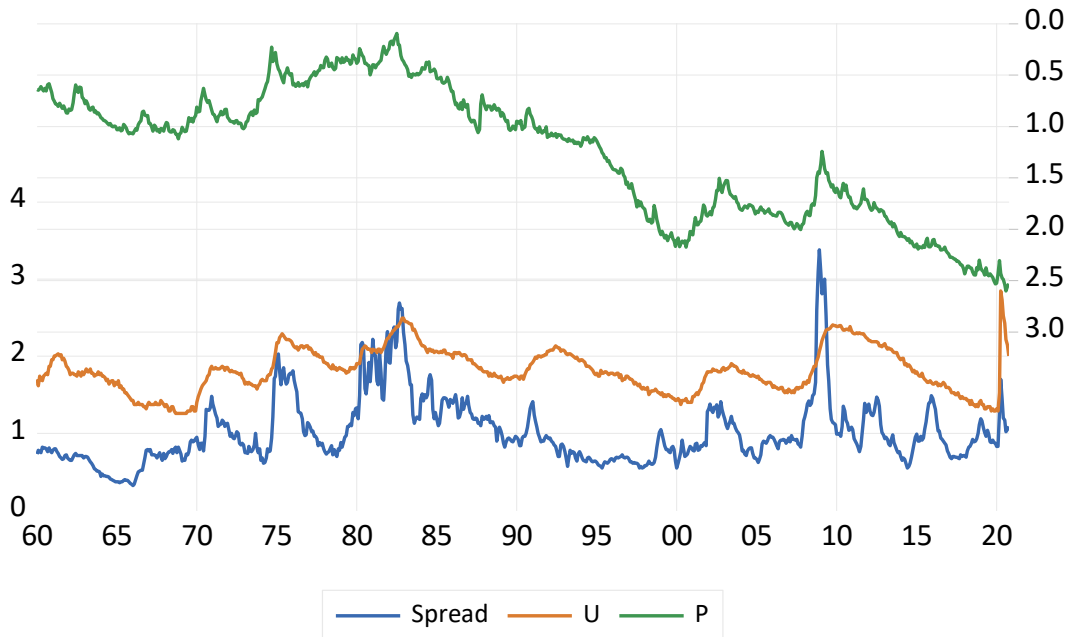
To investigate the links between a macroeconomic "belief function", substituted by stock-market swings and the unemployment rate, we use the same approach as Farmer (2012, 2015). The data from 1960m1 to 2020m10 are calculated as follows:

$$p = \log\left(\frac{S\&P\ 500}{Money\ Wage\ Series}\right), \quad u = \log\left(\frac{100 \times unemployment\ rate}{100 - unemployment\ rate}\right) \quad (1)$$

$p$  represents the stock market (logarithm of deflated stock prices by a measure of the money wage; see Farmer (2010) for more details) and  $u$  represents unemployment (logarithm of a logistic change in the percentage unemployment rate). These changes result in a new set of variables which are unbound above and below. The latter is important, since to be non-stationary, a series has to have the ability to

increase or decrease without bounds, whatever its current value. The unemployment rate comes from the Bureau of Labor Statistics.

In addition, because the stock market can react to other information that forecasts a recession, we take into account the evolution of BAA bonds over ten-year treasuries (source: Federal Reserve Economic Data), like Farmer (2015), Bai (2016) and Petrosky-Nadeau and Zhang (2020).



**Fig 1.** BAA spread, unemployment rate (transformed) and stock market (right axis inverted)

### 3. Methodology

Taking inspiration from and complementing the literature dealing with the connections between the financial market and the labor market, we propose to implement a Granger causality test robust to the presence of instabilities (Rossi and Wang, 2019) to analyze the causal relationship between the stock market and unemployment, by integrating the spread of BAA bonds over ten-year treasuries.

As reported in Stock and Watson (2006) and Rossi (2013), particular challenges are involved in using VAR models and associated methods to infer causality, i.e. instabilities arising from structural breaks and regime shifts (Clark and McCracken, 2006). A potential consequence is that causality relationships occurring between two series may not be integrated within a linear technique of time-invariance estimation. The result would be inaccurate reporting of the significance of traditional VAR-based test statistics based on stationarity (Rossi, 2005). Rossi and Wang (2019) implement the Granger causality test robust to the presence of instabilities. This method has several advantages: it explains instabilities and reestablishes the causality test's statistical significance during the different steps of the sample period; it determines the validity of the test for both reduced-form VAR models and VAR-based direct multistep (VAR-LP) forecasting models; and, in the presence of instabilities, it demonstrates the effectiveness of Granger-causality robust tests compared to standard Granger-causality tests. In

addition, the relationship over time that this tests provides is more suitable than that of a constant-parameter Granger causality method, like in Çepni *et al.* (2020).

The study by Rossi and Wang (2019) demonstrates a reduced-form VAR featuring time-varying parameters:

$$A_t(L)y_t = u_t \quad (2)$$

$$A_t(L) = I - A_{1,t}L - A_{2,t}L^2 - \dots - A_{p,t}L^p \quad (3)$$

$$u_t \sim^{iid}(0, \Sigma) \quad (4)$$

where  $y_t = [y_{1,t}, y_{2,t}, \dots, y_{n,t}]'$  is an  $(n \times 1)$  vector of endogenous variables,  $A_{j,t}$  represents  $(n \times n)$  a coefficient matrix with time-varying properties and  $u_t$  is an error term. By iterating Eq. (3),  $y_{t+h}$  can be projected onto the linear space spanned by  $(y_{t-1}, y_{t-2}, \dots, y_{t-p})'$ , and the following equality can be obtained:

$$y_{t+h} = \Phi_{1,t}y_{t-1} + \Phi_{2,t}y_{t-2} + \dots + \Phi_{p,t}y_{t-p} + \epsilon_{t+h} \quad (5)$$

Where  $\Phi_{j,t}$  is a function of time-varying coefficient matrices (eq(3)) and  $\epsilon_{t+h}$  is a moving average of the errors  $u$  from time  $t$  to  $t+h$ , thus indicating that it is not correlated with the regressors, but rather that it is itself serially correlated (see Jorda (2005) and Rossi and Wang (2019)).

In a next step, we specify  $\theta_t$  as an appropriate subset of  $vec(\Phi_{1,t}, \Phi_{2,t}, \dots, \Phi_{p,t})$ . In both specifications, the Granger causality robust test tries to evaluate whether the following null hypothesis is valid:

$$H_0: \theta_t = 0, \text{ for all } t = 1, \dots, T \quad (6)$$

The test, and the statistics to test  $H_0$ , are based on methodologies established by Rossi (2005). Controlling for both parameter instability and Granger-causality, these tests take into account the robust versions of the mean and exponential Wald tests (*MeanW\** and *ExpW\**; Andrews and Ploberger (1994)), the optimal Nyblom (1989) test (*Nyblom\**), and the Quandt (1960) and Andrews (1993) quaslikelihood-ratio test (*QLR\**).

In this study, the variables included are the unemployment rate ( $u_t$ ), the stock market ( $p_t$ ) and the BAA spread ( $S_t$ ). Their reduced-form VAR is:

$$\begin{bmatrix} u_t \\ p_t \\ S_t \end{bmatrix} = \Phi_1 \begin{bmatrix} u_{t-1} \\ p_{t-1} \\ S_{t-1} \end{bmatrix} + \Phi_2 \begin{bmatrix} u_{t-2} \\ p_{t-2} \\ S_{t-2} \end{bmatrix} + \dots + \Phi_p \begin{bmatrix} u_{t-p} \\ p_{t-p} \\ S_{t-p} \end{bmatrix} + \begin{bmatrix} \epsilon_t^u \\ \epsilon_t^p \\ \epsilon_t^S \end{bmatrix} \quad (7)$$

$$\Phi_j = \begin{bmatrix} \phi_j^{u,u} & \phi_j^{u,p} & \phi_j^{u,S} \\ \phi_j^{p,u} & \phi_j^{p,p} & \phi_j^{p,S} \\ \phi_j^{S,u} & \phi_j^{S,p} & \phi_j^{S,S} \end{bmatrix}, j = 1, \dots, p$$

#### 4. Empirical results

This part presents the causal linkages with the Granger causality test robust to the presence of instabilities between stock market returns, spread and unemployment. Estimations are conducted with the VAR(3) model:  $y_t = [u_t, p_t, S_t]$ . Table 1 shows the results of the time-varying parameter Granger causality test. The null hypothesis of the non-existence of Granger causality, transmitted in a time-varying way from the stock market to unemployment (and vice et versa), is rejected by all tests at traditionally accepted levels.

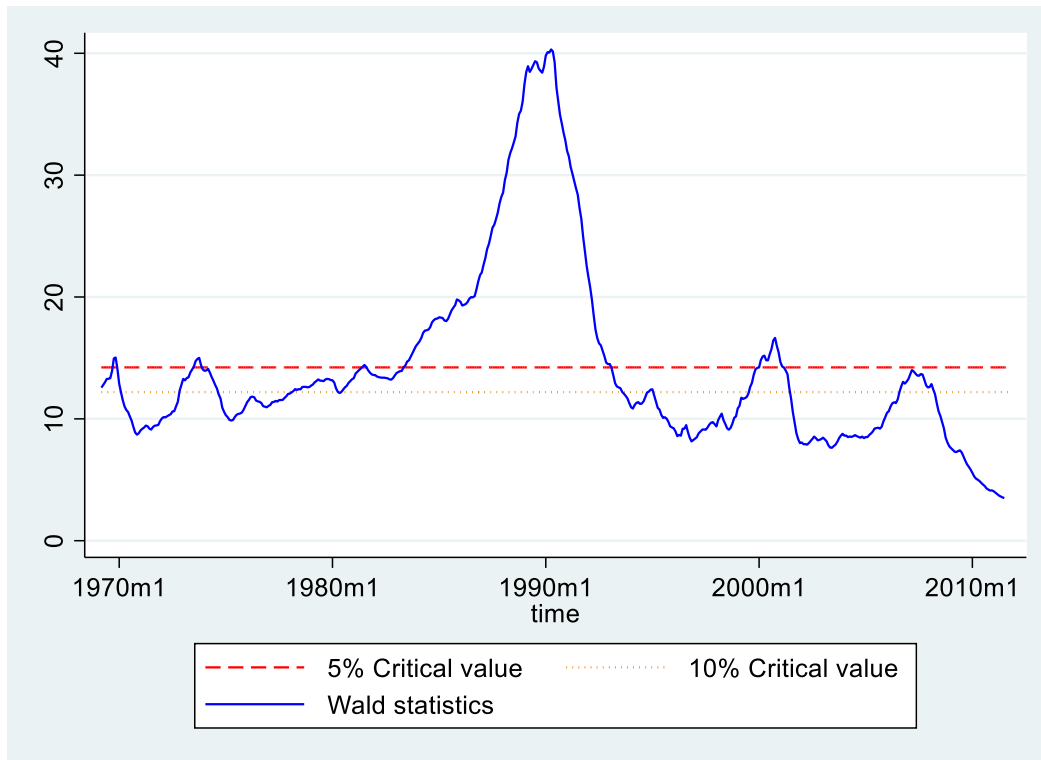
It seems that lagged realizations of “Stock Market” have the ability to predict “Unemployment” in the United States, but that this ability only occurs intermittently. Figure 2 shows the full Wald statistics sequence over time, providing more information about when the Granger-causality takes place. The sequence of the Wald statistics over time  $t$  is greater than the 10% critical value (dashed orange line) during the following periods: the oil crisis and stagflation (1973-75), the double-dip recession (early 1980s) until the post-Reagan spending recession (1990), the dot-com bubble (2001), and the great recession (2007-2009). The peak, in terms of causal relation, seems to occur around the post-Reagan spending recession. The continued decline during the early Reagan years reflected the worsening economy and the sharp rise in unemployment, but in early 1983, the unemployment rate, having peaked at over 10 percent in the country's most severe economic downturn since the Great Depression, began to reverse direction (Lipset and Schneider, 1987). At the same time, stock market activity was intensifying, with an opposite dynamic to that of unemployment (see figure 1). Phelps (1999) demonstrates that the 1990s stock market boom corresponded to a drop in unemployment.

At the same time, lagged realizations of “Unemployment” have predictive power regarding “Stock Market” in the United States, particularly during the 1980s, the dot-com bubble (2001) and the great recession (2007-2009). The predictive capacity of unemployment towards the stock market seems stronger and more persistent during the dot-com bubble compared to great recession. Figure 3 shows a significant causality during the same periods as the causality  $p \rightarrow u$ ; this could reflect a bi-directional causality during the financial and economic crises.

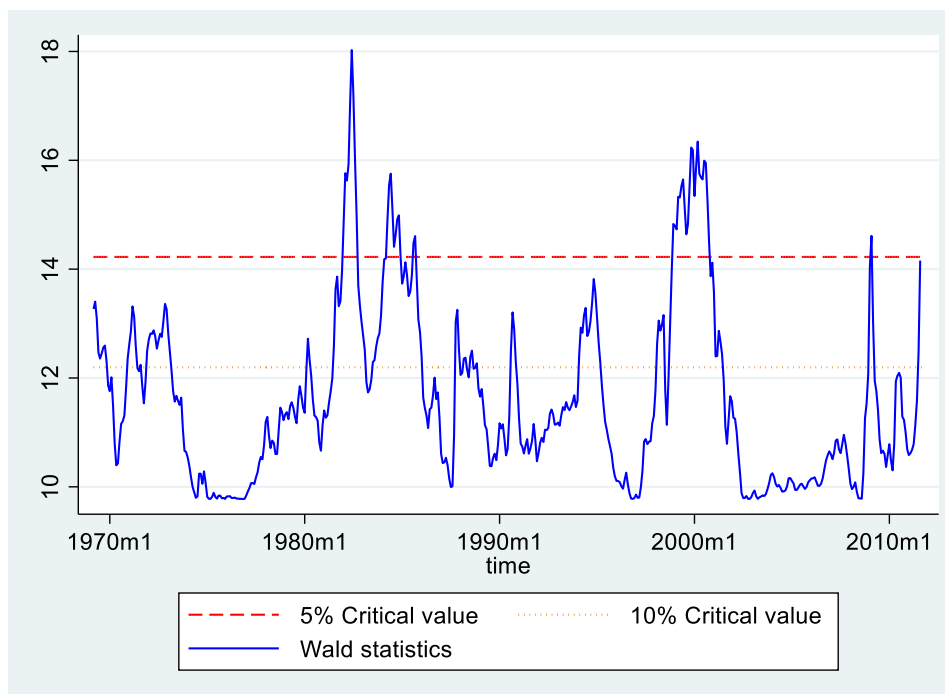
**Table 1**

Time-varying parameter Granger causality test

Causality	Test Type	Test Statistic	P-value
$p \rightarrow u$	ExpW	16.37	0.00
	MeanW	14.23	0.02
	Nyblom	2.07	0.10
	SupLR	40.31	0.00
$u \rightarrow p$	ExpW	6.25	0.01
	MeanW	11.67	0.01
	Nyblom	10.81	0.00
	SupLR	18.02	0.00



**Fig 2.** Wald statistics to test whether stock market ( $p$ ) Granger triggers unemployment ( $u$ )



**Fig. 3** Wald statistics to test whether unemployment ( $u$ ) Granger triggers stock market ( $p$ )



These results extend and contribute to the existing literature by highlighting a bidirectional causality between Stock Market and Unemployment, and by integrating the spread<sup>3</sup>, which is only significant during specific periods. These results are therefore in line with, for example, the work of Boyd *et al.* (2005) because the causality  $u \rightarrow p$  is particularly significant during phases of economic slowdown and / or financial shock, while being relatively limited in time, with an impact that remains transitory (Chen, 2009). Likewise, concerning causality  $p \rightarrow u$ , like Farmer (2015), the stock market seems to contain considerable information that can be used to predict future unemployment rates, notably during the Great Recession. The stock market crash has detrimental economic impacts (Pan, 2020). Concerning the bi-directional causality, the results are consistent with regard to studies by Fritsche and Pierdzioch (2017), Pan (2018) and Sibande *et al.* (2019); significant evidence points to a spillover of information between the stock market and unemployment, even if the countries studied are different.

## 5. Conclusion

In this paper, we employ a recent time-varying causality framework to analyze the interrelations between the stock market and unemployment, and more precisely between the “belief function”, the transformed unemployment rate, and the spread. Time-variability is critical and original to examine the evolution of the relationship over time, in the United States, between 1960 and 2020, especially during a period of high market and economic fluctuations.

Moreover, the results suggest the existence of a bidirectional causality that was particularly significant during the crash periods, with a transient or limited effect over time. These conclusions are in line with the existing literature, such as the work of Boyd *et al.* (2005), Chen (2009), Farmer (2015), Fritsche and Pierdzioch (2017), Pan (2018), Sibande *et al.* (2019), Pan (2020) and Christou *et al.* (2020).

Policymakers could therefore use stock prices to anticipate unemployment, particularly in developed countries (Pan, 2018). Moreover, the boom and the bust cycle of the US economy is key to understanding the spillover of information between stock market fluctuations and the labor market, which could be a particularly important point during and after the health crisis linked to COVID.

---

<sup>3</sup> It should be noted that we obtain similar results with a VAR model:  $y_t = [u_t, p_t]$ .

## 6. References

- Andrews, D. W. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica: Journal of the Econometric Society*, 821-856.
- Andrews, D. W., & Ploberger, W. (1994). Optimal tests when a nuisance parameter is present only under the alternative. *Econometrica: Journal of the Econometric Society*, 1383-1414.
- Bai, H. (2016). Unemployment and credit risk. *Available at SSRN 2788409*.
- Boyd, J. H., Hu, J., & Jagannathan, R. (2005). The stock market's reaction to unemployment news: Why bad news is usually good for stocks. *The Journal of Finance*, 60(2), 649-672.
- Çepni, O., Gül, S., Hacıhasanoğlu, Y. S., & Yılmaz, M. H. (2020). Global uncertainties and portfolio flow dynamics of the BRICS countries. *Research in International Business and Finance*, 54, 101277.
- Chen, S. S. (2009). Predicting the bear stock market: Macroeconomic variables as leading indicators. *Journal of Banking & Finance*, 33(2), 211-223.
- Christou, C., Gabauer, D., & Gupta, R. (2020). Time-Varying impact of uncertainty shocks on macroeconomic variables of the United Kingdom: Evidence from over 150 years of monthly data. *Finance Research Letters*, 37, 101363.
- Clark, T. E., & McCracken, M. W. (2006). The predictive content of the output gap for inflation: Resolving in-sample and out-of-sample evidence. *Journal of Money, Credit and Banking*, 1127-1148.
- Farmer, R. (2010). *Expectations, employment and prices*. Oxford University Press.
- Farmer, R. E. (2012). The stock market crash of 2008 caused the Great Recession: Theory and evidence. *Journal of Economic Dynamics and Control*, 36(5), 693-707.
- Farmer, R. E. (2013). Animal spirits, financial crises and persistent unemployment. *The Economic Journal*, 123(568), 317-340.
- Farmer, R. E. (2015). The stock market crash really did cause the great recession. *Oxford Bulletin of Economics and Statistics*, 77(5), 617-633.
- Feldmann, H. (2011). Stock markets and unemployment in industrial countries. *Applied Economics Letters*, 18(9), 845-849.
- Fritsche U. and Pierdzioch C., (2017). Animal spirits, the stock market, and the unemployment rate: Some evidence for German data, *Economics Bulletin*, 37(1), pages 204-213.
- Fromentin (2021). Cross-border workers in the Greater Region of Luxembourg and financial instability: a non-linear approach. *Applied Economics*, forthcoming.
- Fromentin, V., & Tadjeddine, Y. (2020). Cross-border workers and financial instability: a frequency domain causality analysis applied to the Luxembourg financial centre. *Applied Economics Letters*, 27(4), 280-285.

- Hoon, H. T., & Phelps, E. S. (1992). Macroeconomic shocks in a dynamized model of the natural rate of unemployment. *The American Economic Review*, 889-900.
- Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1), 161-182.
- Lipset, S. M., & Schneider, W. (1987). The confidence gap during the Reagan years, 1981-1987. *Political Science Quarterly*, 102(1), 1-23.
- Nyblom, J. (1989). Testing for the constancy of parameters over time. *Journal of the American Statistical Association*, 84(405), 223-230.
- Pan, W. F. (2018). Does the stock market really cause unemployment? A cross-country analysis. *The North American Journal of Economics and Finance*, 44, 34-43.
- Pan, W. F. (2020). How does the macroeconomy respond to stock market fluctuations? The role of sentiment. *Macroeconomic Dynamics*, 24(2), 421-446.
- Petrosky-Nadeau, N., & Zhang, L. (2020). Unemployment crises. *Journal of Monetary Economics*.
- Phelps, E. S. (1994). Structural slumps: The modern equilibrium theory of unemployment, interest, and assets. Harvard University Press.
- Phelps, E. S. (1999). Behind this structural boom: the role of asset valuations. *American Economic Review*, 89(2), 63-68.
- Phelps, E., & Zoega, G. (2001). Structural booms. *Economic Policy*, 16(32), 84-126.
- Quandt, R. E. (1960). Tests of the hypothesis that a linear regression system obeys two separate regimes. *Journal of the American Statistical Association*, 55(290), 324-330.
- Rossi, B. (2005). Optimal tests for nested model selection with underlying parameter instability. *Econometric Theory*, 962-990.
- Rossi, B. (2013). Advances in forecasting under instability. In *Handbook of economic forecasting* (Vol. 2, pp. 1203-1324). Elsevier.
- Rossi, B., & Wang, Y. (2019). Vector autoregressive-based Granger causality test in the presence of instabilities. *The Stata Journal*, 19(4), 883-899.
- Sibande, X., Gupta, R., & Wohar, M. E. (2019). Time-varying causal relationship between stock market and unemployment in the United Kingdom: Historical evidence from 1855 to 2017. *Journal of Multinational Financial Management*, 49, 81-88.
- Stock, J. H., & Watson, M. W. (2006). Forecasting with many predictors. *Handbook of Economic Forecasting*, 1, 515-554.