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Abstract

This paper studies the empirical relationship between the Federal funds effective rate and the rate of profit or profit-to-capital ratio in the U.S. economy. The linkages between these two variables are studied: 1) at business-cycle frequencies using various filters and employing cross-correlation, regression and simulation analysis; and 2) using Vector Autoregressive models that unveil the dynamic interactions between the variables. The different empirical results reveal that positive shocks in the fed funds interest rate generate negative responses of the rate of profit, thus corroborating previous findings that show that a tight monetary policy is associated with lower aggregate profitability levels.

JEL Classification: E22,E40,E43
Keywords: Fed funds effective real rate, rate of profit, U.S. economy, aggregate profitability.

1 Introduction

A large amount of research has been devoted to the study of the effects of monetary policy shocks on macroeconomic aggregates. However, the effects of monetary policy on different measures of aggregate profitability in the economy have been less well studied since the existing literature has only paid attention to the effects on the log levels of profits and on the share of profits (that is, the profit-to-output ratio) (11, 12, 13, 14). In this sense, the literature has remained silent about the effects of changes in monetary policy on the rate of profit or the rate of return on private investment, *i.e.*, the profit-to-capital ratio. As Feldstein and Summers (23) explain, the latter is a measure of the "social rate of return" —the rate at which forgone current consumption can be transformed into future consumption— on an additional unit of capital invested.[1] This measure of aggregate profitability is relevant since it is a central parameter in order to: 1) explain capital

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[1] Under special technological assumptions about the decay of capital productivity, the rate of profit is in principle equal to the internal rate of return on a marginal investment. The social rate of return is thus equal to the internal rate of return that reduces the present value of the output of the marginal investment to its initial cost (23).

accumulation (22) because the welfare cost of policies that discourage the latter depends on whether the prevailing rate of return is above or below the effective rate of growth of labour force, according to the golden rule of accumulation (16, 43, 44)[2]; 2) study the cost-benefit analysis of public projects that divert funds from private investment through either borrowing or taxation (23); and 3) analyse the causes and consequences of income distribution and business cycle fluctuations. Consequently, the study of the effects of monetary policy on the rate of profit is of paramount importance in order to study the transmission mechanism, and, therefore, to provide new results that can be used for macro-prudential purposes.

The current paper deals with the empirical relationship between the Fed funds effective rate and the profit rate in the U.S. economy during the post-war period. Using data from 1955 (start of Fed funds data) to 2011 (or 2013; depending on which measure of aggregate profitability is used), the interactions between these two variables are studied: 1) at business-cycle frequencies employing cross-correlation, regression and simulation analysis; and 2) using the results obtained from Vector Autoregressive (VAR) models that try to unveil the dynamic interactions between the variables. The different results show that a rise in the rate of interest reduces the rate of profit, thus corroborating previous findings that show that a tight monetary policy hampers aggregate profitability.

Besides this introduction, the rest of the paper is structured as follows. Section 2 reviews some of the literature that has studied the interactions between monetary policy and other measures of profitability; section 3 offers a brief description of the concepts and variables used; section 4 presents the empirical results obtained from the analysis at business-cycle frequencies (section 4.1) and from the VAR models (section 4.2); and, finally, section 5 presents the main conclusions and discusses possible avenues for future research.

2 Related literature

As highlighted in the previous section, the effects of monetary policy shocks on measures of the profit-to-capital ratio have not been studied in the literature. However, there is substantial literature that has studied the effects on different macroeconomic aggregates, including other measures of aggregate profitability such as the log level of profits or the share of profits. In this section we review the most important and recent findings for the U.S. economy with respect to the research question proposed in this paper.

Bernanke and Gertler (8) have analysed the impact of monetary policy on interest payments, profits, gross income and employee compensation of nonfinancial corporate business. Using a quarterly VAR for the period of 1965-1994, they find that a positive innovation of one standard deviation in the funds rate (a tightening of monetary policy) causes a decrease of the log levels of corporate cash flows and profits, calculating that over 40% of the short-run decline in the latter is the result of higher interest payments. They also find that corporate income tends to fall more quickly than costs (such as employee compensation), which tend to be squeezed during a period of monetary tightening. Finally, their results show that the cash squeeze appears to peak about six to

[2] If there is a golden age growth path on which the social net of return to investment equals the rate of growth, then this golden age produces a path of consumption which is uniformly higher than the consumption path associated with any other golden age (16, 43, 44).

nine months after the monetary tightening, about the time that output, inventories and investment begin to decline.[3]

Bernanke and Gertler (8) use the credit channel of monetary transmission in order to explain their results. This mechanism explains that actions taken by the central bank have a direct effect on the external finance premium in credit markets —the difference in cost between funds raised externally (by using equity or debt) and funds generated internally (by retaining earnings)— via the balance sheet and the bank lending channels. The former considers that shifts in Fed policy affect the financial positions of borrowers because increases in interest rates: 1) reduce net cash flows; 2) are typically associated with declining asset prices, which, amongst other things, shrink the value of the borrowers' collateral value; and 3) reduce the spending of customers, reduce the firm's revenue, and, ultimately, erode the firm's net worth and creditworthiness over time. The bank lending channel, in turn, points out the possible effect of monetary policy actions on the supply of loans by depository institutions, particularly loans by commercial banks. Thus, if the supply of bank loans is disrupted for some reason, bank-dependent borrowers may not be literally shut off from credit, but they are virtually certain to incur costs associated with finding a new lender, establishing a credit relationship. This means that a reduction in the supply of bank credit (relative to other forms of credit) is likely to increase the external finance premium and to reduce real activity.[4]

On the other hand, Christiano et al. (11; 13) have studied the effects of contractionary monetary policy shocks (both orthogonalized shocks to the federal funds rate and orthogonalized shocks to the log level of nonborrowed reserves) on different macroeconomic aggregates. Their results show: 1) a delayed response of aggregate output, employment and unemployment; 2) some evidence of an immediate reduction in the log levels of retail sales and corporate profits (both in retail trade and in the nonfinancial sector); and 3) an immediate increment in manufacturing inventories.

In the same vein, Christiano et al. (12) consider various measures of the share of profits in output (real profits to nominal GNP) as well as before-tax profits in five sectors of the economy: manufacturing, durables, nondurables, retail and transportation and utilities. With the exceptions of nondurable goods and transportation and utilities, the evidence shows that a contractionary federal funds policy shock leads to a sharp persistent drop in profits. They proceed to assess the ability of sticky price and limited participation models (in which agents must determine how much money to deposit with financial intermediaries in advance of observing the period's shocks) with frictionless

[3] The effects of the corporate cash squeeze on economic behaviour (investment and spending decisions) depend largely on firm's ability to smooth the drop in cash flows by borrowing. The differential impact of a cash squeeze on different types of firms has been studied by Gertler and Gilchrist (24; 25). In the same vein, movements in the borrower balance sheets can amplify and propagate business cycle fluctuations, a phenomenon that has been referred to as the "financial accelerator" (see Bernanke et al. (9)).

[4] With respect to the balance sheet channel, Bernanke and Gertler (8) provide evidence that links monetary policy to the financial positions of the borrowers using the inverse of the "coverage ratio" (the inverse of the ratio of the sum of interest payments and profits to interest payments by nonfinancial corporations), which is a useful summary measure of a firm's financial condition. They find that increases in the funds rate translate almost immediately into increases in the inverse of the coverage ratio and, ultimately, into weaker balance sheet positions. The literature inaugurated by Christiano et al. (11) has studied in a more detailed way the effects of monetary policy shocks on the borrowing and lending activities of different sectors of the economy using the flow of funds data (see Bonci (10) for a survey on this literature). Finally, regarding the traditional bank lending channel, Bernanke and Gertler (8) point out that its importance has most likely diminished over time because of financial deregulation and innovation.

labour markets to account for these effects, finding that the key failing of the sticky price model is precisely its implication that profits rise after a monetary contraction. This happens because, in this model, a monetary contraction leads to a substantial decline in the resources used by intermediate good producers which, in the absence of labour market frictions or an extremely high elasticity of labour supply, leads to a substantial fall in wages and marginal costs (along with a sharp rise in the mark-up). Thereby, although revenues fall, cost considerations dominate and profits rise.

By contrast, the limited participation model of Christiano et al. (12) can account for the fall in profits but only if one is willing to assume a high labour supply elasticity (around 2%) and a reasonably high mark-up (around 40%). Thereby, Christiano et al. (12) conclude that it is important to embed labour market frictions (which increase the effective elasticity of labour supply) and endogenous capacity utilization since general equilibrium models that allow for only one type of friction (sticky prices or frictions in financial markets) cannot convincingly account for all the facts about how the economy responds to an unanticipated monetary policy shock.

Alexopoulos (1) provides a different version of the standard limited participation model that includes imperfectly observed effort. Her model accounts for the presence of involuntary unemployment, nominal wage rigidity, and the observed responses to monetary policy shocks without appealing to high labour supply elasticities or high mark-ups. The key element in his model is that intermediate good firms detect shirking workers only a fraction of the time and punish them by withholding an increase in their compensation; therefore, the wage that firms need to offer workers to induce the optimal effort level may result in equilibrium unemployment. Compared with standard participation models, unexpected monetary policy shocks have much larger effects on employment and output in the shirking model because the interaction between the frictions in the shirking model (limited participation and imperfectly observed effort) results in optimal nominal wage rigidity.

Both Christiano et al. (12) and Alexopoulos (1) argue that the quantitative response of profits to shocks depends on the way profits are measured. In particular, the ith intermediate good firm's nominal period t profits can be measured as (1):

$$\Pi_{it}^{*} = P_{it}Y_{it} - (\omega R_t + 1 - \omega)\, h_l W_{it} N_{it} - P_t \Theta_t K_{it} \tag{1}$$

$$\Pi_{it} = P_{it}Y_{it} - R_t h_l W_{it} N_{it} \tag{2}$$

where in the equations above P_{it} is the price of the ith intermediate goods; Y_{it} represents the input from the ith intermediate firm; ω is the portion of the wage bill borrowed at the beginning of the period by the intermediate goods firms[5]; R_t is the gross nominal interest rate paid to the financial intermediary on the bank loan; h_l is the fixed number of hours worked per employee; W_{it}, N_{it}, and K_{it} respectively are the nominal wage paid per worker, the number workers hired, and the amount of capital rented by the intermediate good firm i; $P_t = \left[\int_0^1 P_{it}^{1/1-\varpi}\right]^{1-\varpi}$ is the price of the final good, where $\gamma \in [0,\infty)$ is a measure of the substitutability between inputs; and Θ_t is the real rate of return on capital.

Thus, Π_{it}^{*} and Π_{it} respectively represent nominal economic profits and an empirical measure of nominal profits. Intuitively, in these models a contractionary monetary policy shock leaves

[5]When $\omega = 1$, as in the standard limited participation model, the entire wage bill is borrowed at the beginning of the period. However, when $\omega \in (0,1)$, only the portion of wages paid to workers at the beginning of the period need be borrowed from the banks (1).

nominal wages unchanged and decreases the amount of nominal loans to firms. This causes employment to decrease. Although the fall in unemployment cuts the firms' total nominal costs, individuals have less income to spend on goods, so revenue falls. Nominal profits decrease because nominal revenue falls more than nominal costs, and real profits (that is, both Π^*_{it}/P_t and Π_{it}/P_t) fall because of the decrease in nominal profits and the increase in prices.

Christiano et al. (14) provide a dynamic general equilibrium model that incorporates staggered wage and price contracts. Specifically, the model has two key features: 1) it embeds Calvo-style nominal prices and wage contracts; and 2) the real side of the model incorporates four departures from the standard textbook one-sector dynamic growth model: habit formation in preferences for consumption, adjustment costs in investment, variable capital utilization, and assumes that firms must borrow working capital to finance their wage bill. Their model reproduces the dynamic response of inflation and output, and can also account for the hump-shaped response in consumption, investment, profits, and productivity and the weak response of the real wage. They find that: 1) the crucial friction in the model is wage contracts, not price contracts (a version of the model with only nominal wage rigidities does almost as well as the estimated model, and the model with only nominal price rigidities performs very poorly); and 2) it is crucial to allow for variable capital utilization if one wants to generate inertia in inflation and persistence in output.

If we take as given the inertial behaviour of prices and wages, it is useful to focus on the money market-clearing condition (equation (3)) and the household's first-order condition for cash balances (equation (4)) in order to explain the contemporaneous effect of an expansionary monetary policy shock on profits (14):

$$W_t L_t = \mu_t M_t - Q_t \tag{3}$$

$$\upsilon'(q_t) + \psi_t = \psi_t R_t \tag{4}$$

where, in addition to the previously defined variables, W_t is the aggregate wage rate; L_t is the aggregate labour input; μ_t is the monetary policy given by: $\mu_t = \mu + \theta_0 \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots$, where μ is the mean growth rate of money and θ_j is the response of $E_t \mu_{t+j}$ to a t monetary policy shock; M_t is the household's beginning of period t stock of money; Q_t denotes nominal cash balances; $q_t = Q_t/P_t$ denotes real balances[6]; and $\psi_t = \upsilon_t P_t$ is the marginal utility of P_t units of currency, where υ_t is the Lagrange multiplier on the household's budget constraint.

In this model, firms do not wish to absorb any part of a cash infusion because neither W_t nor L_t respond to a policy shock (W_t and L_t are predetermined because W_{it}, consumption, investment, and capital utilization are predetermined by assumption); so that a period t money injection must be accompanied by an equal increase in Q_t. Under the assumption that ψ_t is constant and since P_t is predetermined, the rise in Q_t corresponds to a rise in real balances. According to (4), R_t must fall to induce households to increase q_t.[7] Finally, since R_t falls and the firm's wage bill and revenues are unaffected by the shock, profits must rise.

The conclusion arising from the literature review is that a contractionary (expansionary) monetary policy is accompanied by a decrease (rise) in different measures of profitability. The following sections present empirical evidence of the effects of the interest rate on the rate of profit or the profit-to-capital ratio.

[6] P_t in this model corresponds to $P_t = \left[\int_0^1 P_{it}^{1/1-\varsigma_i}\,\mathrm{d}i\right]^{1-\varsigma_i}$ (14).

[7] In practice, (14) find that ψ_t falls by only a relative small amount.

3 Data and preliminary analysis

We have employed two different estimates of the profit-to-capital ratio (henceforth p_t). In the first place, we use the computation of p_t provided by Duménil and Lévy (18): $p_t^A = (\mathrm{NDP} - wL)/\mathrm{KN}$; where NDP represents Net Domestic Product (extracted from the U.S. National Income and Product Accounts (NIPA)); $w = \mathrm{NTOTW}/\mathrm{NWEMPL}$ is a measure of the annual compensation per employee, where NTOTW and NWEMPL respectively represent the compensation of employees and the full-time equivalent employees in private industries (both series were retrieved from the NIPA tables); $L = \mathrm{NWEMPL} + \mathrm{NSELF}$ denotes total private employment, where NSELF denotes self-employed persons (also obtained from the BEA)[8]; and KN denotes the private net fixed capital stocks, which has been restricted to equipment and structures (obtained from the BEA capital stock tables). This measure of p_t is available until 2011.[9]

In second place, we have used an estimate of the pretax net rate of return on additional private corporate investment (22, 23, 46).[10] For this measure we have only considered considered corporate profits —that is, without interest payments— to the value of the capital stock in the nonfinancial corporate sector. We have done so in order to use a different measure of p_t^A since, by definition, the latter includes interest payments. Thereby, for this rate of profit we have: $p_t^B = \mathrm{CP}/\mathrm{KN}(-1)$; where CP denotes corporate profits with IVA and CCAdj (Table 1.14 from NIPA, line 27) and KN is the current-cost net stock of private fixed assets of the nonfinancial corporate business sector (Table 6.1 from NIPA, line 4). In this case, we employed the current-cost nonfinancial corporate capital stock of the previous year ($\mathrm{KN}(-1)$) since the NIPA lists the capital stock at the end of the year, and we have calculated p_t^B until 2013.

Both p_t^A and p_t^B are similar to the ones used by Feldstein and Summers (23) and Poterba (46) for the nonfinancial corporate sector in the U.S. economy. For the period 1948-1976, Feldstein and Summers (23) calculate that the net p_t (computed as the ratio of profits plus interest payments to the value of real capital including fixed capital, inventories, and land) is 10.6%; whereas Poterba (46) considers the rate of return to corporate tangible assets in the U.S. economy for the period 1959-1996 (he calculates CP as profits before tax with IVA and CCAdj plus net interest payments plus property taxes) and estimates that the average pretax rate of return over the period 1959-1996 is approximately 8.5%.[11]

Regarding the interest rate, we use the fed funds effective rate. Both p_t^A and p_t^B represent real measures since both the numerator —a current-dollar profit flow— and the denominator —

[8]Therefore, wL represents the total remuneration to labour including a correction for the wage-equivalent of self-employed persons.

[9]This measure of p_t was also employed by Duménil et al. (17) with a few minor alterations. The full data set can be found at: http://www.jourdan.ens.fr/levy/uslt4x.txt.

[10]As Feldstein and Summers (23) explain, the pretax rate of return is an appropriate concept regarding the analysis in the return that the nation earns on private investment. To understand the saving and portfolio behaviour of individual investors it would be necessary to examine the after-tax rate of return.

[11]On the other hand, using calibration procedures for the U.S economy, Greenwood et al. (29) find a pre-tax real return of 20.5%; whereas Gomme and Rupert (26) compute a profit rate of 13.2% per annum and an after-tax real return of 7.5%. In a very recent article, Gomme and Rupert (27) construct a quarterly measure of real net after-tax rate of return to business capital for the U.S. using the NIPA. They find that: 1) the mean of this measure is 5.16% for the period of 1954-2008; and 2) the Standard and Poor 500 return is roughly six times more volatile than this measure. They point out that, since the returns to capital and equity are identical in the neoclassical growth model, a theory of the stock market that breaks the equivalence between the returns to equity and capital is needed.

a current-cost capital stock— reflect the same set of prices. This means that, in order to study the effects of the interest rate on the rate of profit, the relevant comparison between the variables needs to take into account the real rate of interest (henceforth r_t). The latter has been calculated as follows: $r_t = \left[\frac{1+I_t}{1+\mathrm{inf_t}} - 1\right] 100$; where I_t is the nominal Federal Funds effective rate (extracted from the Federal Reserve System electronic database), and $\mathrm{inf_t}$ is the inflation rate measured by the US GDP implicit price deflator (2009=100; extracted from the BEA database).[12]

Finally, we have employed annual data for the empirical analysis since the series for p_t^A and for KN (needed to construct p_t^B) are only available at annual frequencies. Figure 1 plots p_t^A, p_t^B, and r_t, covering the macro history of the US over the last five decades: 1955-2013. On inspection, it is possible to observe that both p_t^A and p_t^B have been systematically above r_t, so that it is possible to assert that p_t can be considered as an upper limit to r_t during the period of study. The statistical summary of both variables presented in Table 1 reveals that both series present similar standard deviations and that the null hypothesis of normality of the Jarque-Bera test is not rejected for the series at the 5% level.

[INSERT FIGURE 1 ABOUT HERE]
[INSERT TABLE 1 ABOUT HERE]

4 Empirical results

The following sections present the empirical evidence of the relationship between the fed funds interest rate and the two measures of the rate of profit.

We first examine the r_t-p_t relationship at business-cycle frequencies using cross-correlation, regression and simulation analysis. The cyclical component (henceforth c_t) of the series has been computed using different filters in order to test the robustness of the results: Hodrick-Prescott (HP) (32), Baxter-King (BK) (7), Christiano-Fitzgerald (CF) (15), and a digital Butterworth (Bw) (28, 45) filter. We also report the results obtained using a first-difference (FD) filter.

In the second part of this section we analyse the relationship between r_t and p_t using VAR models. We first carried out four linear unit root tests on the r_t and p_t series in order to determine its order of integration; and then we estimate the VAR models and present the main descriptive statistics together with the structural inference analysis.

4.1 Business-cycle frequencies analysis

4.1.1 Filters employed

This section offers a succinct description of the different filters employed, paying special attention to the Bw filter since the latter has received less attention in applied research. If y_t is the finite series of interest (that is, either r_t or p_t in our case), then its respective c_t is:

$$c_t = \sum_{j=-n_1}^{n_2} \widehat{b}_j y_{t-j} \tag{5}$$

[12]As Taylor (53) explains, the distinction between real interest rates and nominal interest rates is crucial when studying the monetary transmission mechanism. We work under the assumption that the Fed has leverage over the short-term real rate because prices are sticky (8).

where $\widehat{b}_j$ are the coefficients of the finite impulse-response sequence of the filter. This sequence is the inverse Fourier transform of either a square wave (if the filter is a band-pass, such as the BK and CF) or step function (if the filter is a high-pass, such as the HP and Bw).

In the frequency domain, it is possible to establish the following relationship between the finite estimates of c_t ($\widehat{c}(w)$) and the frequency transfer function of the filter $\widehat{B}$ ($\widehat{B}(w)$):

$$\widehat{c}(w) = \widehat{B}(w)y(w) \tag{6}$$

where w denotes the frequencies.

The frequency transfer function for $\widehat{B}(w)$ can be expressed in polar form as:

$$\widehat{B}(w) = |B(w)| \exp\{\iota\theta(w)\} \tag{7}$$

where ι is the imaginary number $\iota = \sqrt{-1}$, and $|B(w)|$ and $\theta(w)$ respectively represent the filter's gain function (which determines if the amplitude of the stochastic cycle is increased or decreased at a particular frequency) and the filter's phase function (which determines how a cycle at a particular frequency is shifted forward or backward in time).

The band-pass filters employed in this paper (BK and CF) use a square wave as the transfer function, so that: $B(w) = \begin{cases} 1, & \text{if } |w| \in [w_l, w_h] \\ 0, & \text{if } |w| \notin [w_l, w_h] \end{cases}$, where w_l and w_h respectively denote the lowest and highest frequencies employed. In turn, the high-pass filters employed (HP and Bw) use a step function, so that: $B(w) = \begin{cases} 1, & \text{if } |w| \geq w_h \\ 0, & \text{if } |w| < w_h \end{cases}$.

On the other hand, the digital Bw filter is a two-parameter high-pass filter. One parameter determines the cutoff period and sets the location where the gain function starts to filter out the high-period (low-frequency) stochastic cycles; whereas the other parameter determines the order of the filter (henceforth m) and sets the slope of the gain function for a given cutoff period.[13] Pollock (45) has shown that the gain of the Bw filter ($\xi(w)$) is given by:

$$\xi(w) = \left[1 + \left\{\frac{\tan\left(\frac{w_c}{2}\right)}{\tan\left(\frac{w}{2}\right)}\right\}^{2m}\right]^{-1} \tag{8}$$

where $w_c = \frac{2\pi}{\varphi_h}$ is the cutoff frequency, and φ_h is the maximum period of cycles filtered out.

The model that corresponds to the Bw filter represents y_t in terms of zero mean, covariance stationary, and independent and identically distributed shocks v_t and d_t:

$$y_t = \frac{(1+L)^m}{(1-L)^m} v_t + d_t \tag{9}$$

where L is the lag operator.

[13] For a given cutoff period, the slope of the gain function at the cutoff period increases with m; whereas for a given m, the slope of the gain function at the cutoff period increases with the cutoff period. The existence of two parameters provides additional flexibility in order to compute the c_t of the series compared with the HP filter (28, 45). Indeed, the HP filter is a one-parameter high-pass filter since it possesses only a single adjustable parameter which sets both the location of the cutoff frequency and the slope of the gain function.

From this model, Pollock (45) shows that the optimal estimate for the cyclical component ($\mathbf{c}$) is:

$$\mathbf{c} = \lambda \mathbf{Q}(\Omega_L + \lambda \Omega_H)^{-1}\mathbf{Q}'\mathbf{y} \tag{10}$$

where $\text{Var}\{\mathbf{Q}'(\mathbf{y}-\mathbf{c})\} = \sigma_\nu^2 \Omega_L$ and $\text{Var}\{\mathbf{Q}'\mathbf{c}\} = \sigma_\varepsilon^2 \Omega_H$; Ω_L and Ω_H are symmetric Toeplitz matrices with $2m+1$ nonzero diagonal bands and generating functions $(1+z)^m(1+z^{-1})^m$ and $(1-z)^m(1-z^{-1})^m$, respectively; the matrix $\mathbf{Q}'$ is a function of the coefficients in the polynomial $(1-L)^d = 1+\delta_1 L + \ldots + \delta_d L^d$ (see Stata (52)); and the parameter λ is a function of φ_h and m such that:

$$\lambda = \left\{\tan\left(\frac{\pi}{\varphi_h}\right)\right\}^{-2m} \tag{11}$$

Finally, it can be shown that $\Omega_H = \mathbf{Q}'\mathbf{Q}$ and $\Omega_L = |\Omega_H|$, which simplifies the final calculation of the c_t of the series to:

$$\mathbf{c}^* = \lambda \mathbf{Q}\left\{|\mathbf{Q}'\mathbf{Q}| + \lambda(\mathbf{Q}'\mathbf{Q})\right\}^{-1}\mathbf{Q}'\mathbf{y} \tag{12}$$

The different c_ts of the series were extracted as follows. With respect to the HP filter, we followed the suggestion proposed by Ravn and Uhlig (48) for annual data, so that the smoothing parameter was selected to be 6.25. We employed three years of data in order to construct the BK filter, using 2 and 8 years as the minimum and maximum periodicities to be included in the filtered series, as suggested by Baxter and King (7). Regarding the Bw filter, we employed a second order version of the filter, filtering out stochastic cycles at periods larger than 8. Finally, for the full sample asymmetric CF filter we used the same minimum and maximum periodicities employed for the BK filter, considering p_t as an $I(1)$ unit root process and r_t as an $I(0)$ covariance stationary process.[14]

4.1.2 Cross-correlation analysis

We now present the results of the cross-correlation analysis used to explore the co-movements between r_t and p_t. It is possible to say that the cyclical component of the rate of interest (henceforth c_t^r) is leading by κ-years, is synchronous, or is lagging by κ-years the cyclical component of the rate of profit (henceforth c_t^p), if the correlation coefficients $\text{Corr}(c_t^p, c_{t-\kappa}^r)$, $\text{Corr}(c_t^p, c_t^r)$, $\text{Corr}(c_t^p, c_{t+\kappa}^r)$, respectively, adopt the largest value at that year. In the same vein, a positive (negative) and significant value indicates that c_t^r and c_t^p move in the same (opposite) direction, and a number close to zero indicates that both cyclical components are uncorrelated.

These results are presented in Table 2. The first part of the Table shows the results obtained using p_t^A for the period 1955-2011; whereas the second part shows the results obtained using p_t^B for the period 1955-2013. In the first place, it is possible to observe that the highest statistically significant correlation value is $\text{Corr}(c_t^p, c_{t-1}^r)$, so that c_t^r leads c_t^p by one year. The highest correlation value is given by the BK filter, whereas the lowest correlation value appears when the FD filter was employed. In general, the correlation values do not seem to be high, particularly when p_t^B was considered.

In second place, we find that the value of $\text{Corr}(c_t^p, c_{t-1}^r)$ shows that the relationship between c_t^p and c_t^r is negative, considering both p_t^A and p_t^B.

[14] As shown in section 4.2.1, the different unit root tests show that $p_t \sim I(1)$ and $r_t \sim I(0)$. Moreover, if r_t is assumed to be an $I(1)$ process, then the cyclical component obtained via the CF filter is very similar to the one here presented (series available on request).

[INSERT TABLE 2 ABOUT HERE]

4.1.3 Regression analysis, parameter stability and Granger non-causality tests

Having established that c_t^r leads c_t^p, we proceed to analyse the link between these two variables in the context of a simple backward-looking regression model in order to evaluate the rate of interest as a predictor variable, using both in-sample and out-of-sample Granger non-causality tests:

$$c_t^p = \alpha + \beta c_{t-1}^p + \gamma c_{t-1}^r + \eta_t \tag{13}$$

where η_t is the error term.

The estimation results of equation (13) using both p_t^A and p_t^B with the different filters are reported in Table 3. From the latter it is possible to see that the standard diagnostic tests are satisfied in all cases at the 10% level of significance; and that the parameter γ is statistically significant at the 1% level. We find that $\gamma < 0$ in all cases, so that we conclude that the results obtained via the cross-correlation analysis corroborate the ones presented in the previous section: an increase in r_t above its trend generates a decrease in p_t below its respective trend.

[INSERT TABLE 3 ABOUT HERE]

However, one possible problem with the estimation of equation (13) may be that the parameters are not stable over time, which is particularly relevant given the Lucas (35) critique and the backward-looking nature of the model. Thus, we have used a battery of endogenous structural break tests in order to take into account this possibility: the Supremum or Maximum F (SupF) test, the Average F (AvgF) test, and the exponential F (ExpF) test (2, 3); one multiple break test (4, 5); the parameter constancy test of Hansen (30); and the Elliot-Muller test (21). An exposition of the different tests is presented in appendix A, and El-Shagi and Giesen (19) provide a comparison of the power and size properties of various of the structural stability tests employed.

The first three tests (SupF, AvgF and ExpF) were computed over all possible break dates within 15% trimmed data (that is, in the central 85% of the sample), so that we test the null hypothesis of no breakpoints within 15% trimmed data. We have used the generalization of the Quandt-Andrews (2)'s test for the Bai and Perron (4; 5), which was carried out setting the maximum number of breaks equal to 5 and the trimming percentage to 15% in all cases. For the latter we only report the equal-weighted version of the test (UDMax) in Table 4, which chooses the alternative that maximizes the statistic across the number of breakpoints.[15]

The results of the different stability tests of equation (13) are presented in Table 4 below. The null hypothesis of the tests (joint parameter stability) is not rejected at the 1% level of significance in most cases (the only exceptions are the qLL test for the case of the BK filter estimation when p_t^B was used and Hansen (30)'s test since in both cases the null hypothesis is not rejected only at the 10% level). Therefore, we can conclude that the great majority of results show that the regression coefficients obtained from the estimation of equation (13) are stable over the sample.

[INSERT TABLE 4 ABOUT HERE]

[15]The weighted approach of the test (WDMax) (which applies weights to the individual statistics, so that the implied marginal probabilities are equal prior to taking the maximum) yields fairly similar results. These results are also available on request.

Having corroborated the parameter stability of the estimates, we now analyse if the rate of interest can be considered as a predictor variable of the profit rate. Hence, we use both in-sample and out-of-sample Granger causality F-tests in order to test the null hypothesis that $\gamma = 0$. Regarding the out-of-sample Granger causality test, we have employed the test proposed by McCracken (37). The latter consists in comparing the predictive ability of equation (13) (that is, the equation that includes c^r_{t-1}) with the predictive ability of its restricted version (that is, the equation that excludes c^r_{t-1}). The Mean Squared Prediction Error (MSPE) has been used as a measure of prediction performance.[16] Thus, the general representation of the McCracken F-test of forecast accuracy ($\mathrm{MSPE_F}$) is the following:

$$\mathrm{MSPE_F} = S\left(\frac{S^{-1}\sum_{t=T}^{n}\left(\widehat{u}^2_{1,t+1} - \widehat{u}^2_{2,t+1}\right)}{S^{-1}\sum_{t=T}^{n}\widehat{u}^2_{2,t+1}}\right) = P\left(\frac{\mathrm{MSPE_1} - \mathrm{MSPE_2}}{\mathrm{MSPE_2}}\right) \tag{14}$$

where S is the number of forecasts, T is the number of observations included in the forecast, $\widehat{u}_{1,t+1}$ and $\widehat{u}_{2,t+1}$ are respectively the 1-step ahead forecast errors from the restricted model (model without c^r_{t-1}) and from the unrestricted model (model with c^r_{t-1}), so that $\sum_{t=T}^{n}\widehat{u}^2_{1,t+1} = \mathrm{MSPE_1}$ and $\sum_{t=T}^{n}\widehat{u}^2_{2,t+1} = \mathrm{MSPE_2}$.

If the $\mathrm{MSPE_2}$ is significantly lower than $\mathrm{MSPE_1}$, then this would imply that the rate of interest causes the rate of profit. For the out-of-sample tests using p^A_t (p^B_t) we have split the sample at 2006 (2002) and evaluated the forecast accuracy of the models over the period 2007-2011 (2003-2007).[17]

The results of both in-sample and out-of-sample tests are reported in Table 5. The former shows that the null hypothesis (c^r_{t-1} does not Granger cause c^p_t) is strongly rejected in all cases. On the other hand, the out-of-sample tests shows that $\mathrm{MSPE_2}$ is smaller than $\mathrm{MSPE_1}$ in all cases. The estimated McCracken F-tests are higher than the critical values at all significance levels, which means that the null hypothesis of the out-of-sample test is also strongly rejected (the only exception being the results obtained from the Bw filter using p^A_t since the null hypothesis is rejected only at the 10% level). Therefore, we can conclude that, at business cycle frequencies, the rate of interest Granger causes the rate of profit according to both in-sample and out-of-sample causality tests.

[INSERT TABLE 5 ABOUT HERE]

4.2 VAR analysis

4.2.1 Unit root tests

We now proceed to analyse the relationship between the rates of interest and profit using VAR models. We first employ four different unit root tests in order to determine the order of integration of the series: Augmented Dickey-Fuller (ADF; Said and Dickey (50)); Dickey–Fuller Generalized Least Squares (DF-GLS; Elliott at al. (20)); modified Phillips-Perron (PP) tests (40); and KPSS stationarity test (33).

[16] We did not apply a recursive regression approach to forecasting since, as shown before, equation (13) does not exhibit parameter instability.

[17] We decided to separate the samples at different periods in order to test the robustness of the results. For the forecasts using p^B_t we decided not to consider the recent period of economic crisis (2008-2013).

The highest lag order (l_{max}) selected in order to carry out the tests was determined from the sample size according to the method proposed by Schwert (51), so that $l_{max} = 10$; whereas the optimal lag order (l^*) was selected according to the Modified Akaike Information Criterion (MAIC) proposed by Ng and Perron (40) since this criterion reduces size distortions substantially.[18] We have employed OLS-detrended data as the AR spectral estimation method for the Ng-Perron tests since the latter can be considered a solution to the drawback that, for non-local alternatives, the power of the Ng and Perron (40) tests can be very small (41); whereas the estimate of the long-run variance in the KPSS tests was computed using GLS-detrended data.

In Table 6 we report the different unit root tests that best capture the actual behaviour of the series in order to avoid misspecification. Thereby, the tests were carried out including a constant and a trend as exogenous regressors for the case of the p_t series; whereas we only included a constant for the case of the r_t series.[19] With respect to the p_t series, it is possible to observe that none of the ADF, DF-GLS, and Ng-Perron tests is able to reject the null of a unit root; and that the null hypothesis of the KPSS tests (p_t is a stationary process) is strongly rejected. On the other hand, the unit root tests reject both the null hypothesis of a unit root for the case of the r_t series (with the exception of the ADF test) and the null hypothesis of the KPSS test (r_t is a stationary process).

Given that the DF-GLS and the Ng-Perron tests can have substantially higher power than the traditional unit root tests (54), we conclude that the p_t series can be characterized as an $I(1)$ process: p_t^A, $p_t^B \sim I(1)$; whereas r_t can be characterized as an $I(0)$ process: $r_t \sim I(0)$.[20]

[INSERT TABLE 6 ABOUT HERE]

4.2.2 VAR models

We have included both Δp_t and r_t in order to work with 2 variable VAR models in which the variables have the same order of integration:

$$\mathbf{Y_t} = \mathbf{A} + \mathbf{B(L)}\mathbf{Y_t} + \Upsilon_t \tag{15}$$

where $\mathbf{Y_t} = (\Delta p_t, r_t)'$, $\mathbf{A}$ is a 2X1 vector of constant terms, $\mathbf{B(L)}$ is a 2X2 matrix polynomial of unrestricted constant coefficients in the lag operator L, and Υ_t is a 2X1 vector of white noise error terms with covariance matrix $\sum_\Upsilon$.

We estimate two different VAR models, one including Δp_t^A and another one including Δp_t^B over the periods of 1955-2011 and 1955-2013, respectively. In both cases the different information criteria (Akaike, Schwarz, Hannan-Quinn, and the sequential modified LR test statistic) indicate that the optimal lag length for the VAR models is two. These VAR models: 1) are stable since all roots have modulus less than 1 and lie inside the unit circle; 2) do not present problems of autocorrelation, heteroskedasticity or normality according to the individual and joint misspecification tests (see Tables B1 and B2 in the appendix); and 3) do not show parameter

[18] The results obtained following the general-to-specific approach proposed by Ng and Perron (39) are fairly similar to the ones here presented.

[19] Different specifications did not change the main conclusions (results available on request)

[20] The latter corroborates recent empirical evidence that finds that different r_t do not contain a unit root, but exhibit substantial persistence —shown by extended periods when real interest rates are substantially above or below the sample mean— instead (see Lee and Tsong (34), Neely and Rapach (38), Rapach and Wohar (47)).

instability according to the joint parameter stability tests employed in the previous section (see Table B3 in the appendix).[21]

Tables 7 and 8 respectively present the Granger non-causality tests and the forecast error variance decompositions of the VAR models. In the first place, the former shows that the lagged values of r_t help to predict movements of both Δp_t^A and Δp_t^B at the 1% level of significance since the null hypothesis of no Granger causality is strongly rejected in this case. Δp_t^A also seems to contain information that helps to predict movements in r_t at the 10% level of significance; whereas it is not possible to reject the null hypothesis of no Granger causality when Δp_t^B was employed.

[INSERT TABLE 7 ABOUT HERE]

In second place, from Table 8 it is possible to observe that, as the forecast horizon approaches 6 lags, higher portions of the variation of both Δp_t^A and Δp_t^B can be explained by shocks from r_t. [22]

[INSERT TABLE 8 ABOUT HERE]

In Figures 2 and 3 we present the impulse response functions (IRFs) together with its respective 0.68 error bands obtained via Monte Carlo simulations (2000 replications in all cases), as suggested by Sims and Zha (49). Figure 2 presents the IRFs of the VAR including Δp_t^A; whereas Figure 3 shows the IRFs of the VAR including Δp_t^B. The IRFs were obtained: 1) by identifying the shock structure using Choleski factorization of the variance of Υ_t following the ordering listed in $\mathbf{Y_t}$ (this means that this orthogonalization of innovations employs the assumption that there is no contemporaneous effect of the innovation in r_t on Δp_t); and 2) via the procedure described by Pesaran and Shin (42), so that these represent the generalized impulse response functions (GIRFs) that do not require the orthogonalization of shocks and are invariant to the ordering of the variables in the VAR.

[INSERT FIGURE 2 ABOUT HERE]
[INSERT FIGURE 3 ABOUT HERE]

The results show very similar dynamic patterns of interaction amongst both variables in all cases. If we assume that disturbances to the funds-rate equation in the VAR are shocks to monetary policy then it is possible to interpret the responses of Δp_t to a funds-rate shock as the structural responses of this variable to an unanticipated change in monetary policy. The lower-left graphs show the IRFs of an innovation in r_t on Δp_t, indicating that a positive shock to the former causes a negative effect on the latter that turns insignificant after 1 year in both cases.[23]

Finally, Figures 4 and 5 show the accumulated responses of Δp_t^A and Δp_t^B to its own innovations and to innovations in r_t. The results reveal similar shapes of these functions, showing

[21] In Table B3 we only report the L_c statistic of Hansen (30) and the qll statistic of Elliott and Müller (21) in order to present the most robust results. With the exception of the Bai-Perron's UDMax test (which shows mixed results), the conclusions obtained using the other parameter stability tests employed in the previous section (SupF, AvgF, ExpF) are fairly similar (these results are available upon request).

[22] The forecast error variance decomposition results obtained using the other possible VAR ordering (that is, $r_t \rightarrow \Delta p_t$) yield similar conclusions (results are available upon request).

[23] The IRFs obtained by identifying the shock structure using the inverse Cholesky factorization ($r_t \rightarrow \Delta p_t$) are also fairly similar. These are shown in Figures C1 and C2 in the appendix.

that the accumulated responses obtained via the GIRFs are slightly larger than the Cholesky-based accumulated responses. It is possible to observe that the accumulated response of Δp_t^B to an innovation in r_t is more persistent than the one associated with Δp_t^A.

[INSERT FIGURE 4 ABOUT HERE]
[INSERT FIGURE 5 ABOUT HERE]

4.2.3 Long-run structural inference

We finally study the interaction between these two variables in the long-run. The bivariate moving average representation of both series is the following:

$$\Delta p_t = \sum_{l=0}^{\infty} c_{11}(l)\varepsilon_{p,t-l} + \sum_{l=0}^{\infty} c_{12}(l)\varepsilon_{r,t-l} \tag{16}$$

$$r_t = \sum_{l=0}^{\infty} c_{21}(l)\varepsilon_{p,t-l} + \sum_{l=0}^{\infty} c_{22}(l)\varepsilon_{r,t-l} \tag{17}$$

So that the matrix representation is the following:

$$\mathbf{Y_t} = \mathbf{C(L)}\varepsilon_\mathbf{t} \tag{18}$$

where $\mathbf{C(L)} = \begin{bmatrix} C_{11}(L) & C_{12}(L) \\ C_{21}(L) & C_{22}(L) \end{bmatrix}$, and $\varepsilon_\mathbf{t} = (\varepsilon_{p,t}, \varepsilon_{r,t})'$. Thereby, $C_{ij}(L)$ are polynomials in L with individual coefficients denoted by $c_{ij}(l)$, $\varepsilon_\mathbf{t}$ is the vector of white noise innovations with covariance matrix $\sum_\varepsilon$, and $\varepsilon_{p,t}$ and $\varepsilon_{r,t}$ respectively denote the exogenous shocks to p_t and r_t.

We assume that the interaction between both variables is null in the long-run; therefore, we have used two different long-run structural identification assumptions in order to test the robustness of the results:

$$C_{21}(L) = \sum_{l=0}^{\infty} c_{21}(l) = 0 \tag{19}$$

$$C_{12}(L) = \sum_{l=0}^{\infty} c_{12}(l) = 0 \tag{20}$$

Equations (19) and (20) respectively depict the cases where the cumulative effect of an $\varepsilon_{p,t}$ shock on r_t must equal to zero and where the cumulative effect of an $\varepsilon_{r,t}$ shock on Δp_t must equal to zero.

The impulse responses of the VARs using Δp_t^A and Δp_t^B are respectively presented in Figures 6 and 7, together with its respective 68% confidence intervals. In the same vein, Figures 8 and 9 show the accumulated responses of Δp_t^A and Δp_t^B using the identification assumptions depicted in equations (19) and (20). It is possible to observe that the results obtained are very similar between them; and also fairly similar to the IRFs and to the cumulative IRFs shown in Figures 2 to 5. Hence, the results obtained are robust to the short-run and long-run identifying assumptions employed, and it is possible to conclude that a positive innovation in the rate of interest generates a negative response of the rate of profit.

[INSERT FIGURE 6 ABOUT HERE]
[INSERT FIGURE 7 ABOUT HERE]
[INSERT FIGURE 8 ABOUT HERE]
[INSERT FIGURE 9 ABOUT HERE]

5 Conclusions and future research

The present paper has studied the effects of a monetary policy shock, measured by a rise in the Federal Funds effective rate, on the profit rate or the profit-to-capital ratio in the postwar economy of the United States. In the first place, the analysis was carried out at business cycle frequencies using various filters. The results indicate that the cyclical component of the rate of interest leads the cyclical component of the rate of profit by one year and that the relationship between both variables is negative. The real rate of interest-rate of profit link is stable according to a battery of different endogenous structural break tests; and both in-sample and out-of-sample Granger non-causality tests show that the cyclical component of the rate of interest can be considered as a predictor variable of the cyclical component of the rate of profit.

In second place, using bivariate VAR models we find that there is evidence of interaction between the fed funds rate of interest and the profit rate according to the main descriptive statistics of these models (Granger non-causality tests and forecast error variance decomposition analysis). In the same vein, the different impulse response functions show that a positive shock in the rate of interest generates a negative response of the rate of profit that turns statistically non-significant approximately after one year. This result is robust to different ways in which the innovations are orthogonalized both in the short and long-run.

Therefore, the conclusion arising from the different tests is that a tight monetary policy generates lower levels of the profit-to-capital ratio and, thereby, lower levels of aggregate profitability. There are, however, different ways in which it is possible to extend the current research in order to provide more detailed facts about the quantitative and qualitative effects of monetary policy on aggregate profitability levels. One possible extension is to enlarge the system to include other relevant variables, such as the 10-year government bond yield, investment or exchange rates. Another possibility is to study the effects of other measures of monetary policy on the rate of profit, such as nonborrowed reserves or the rate of money growth (for example, the M2 monetary aggregate), which may incorporate the effects of possible changes in reserve-market structure and in the Fed's operating procedures. In this sense, it is also necessary to develop further theoretical models that take into account the effects of monetary policy on the profit rate. We leave all these topics for future research.

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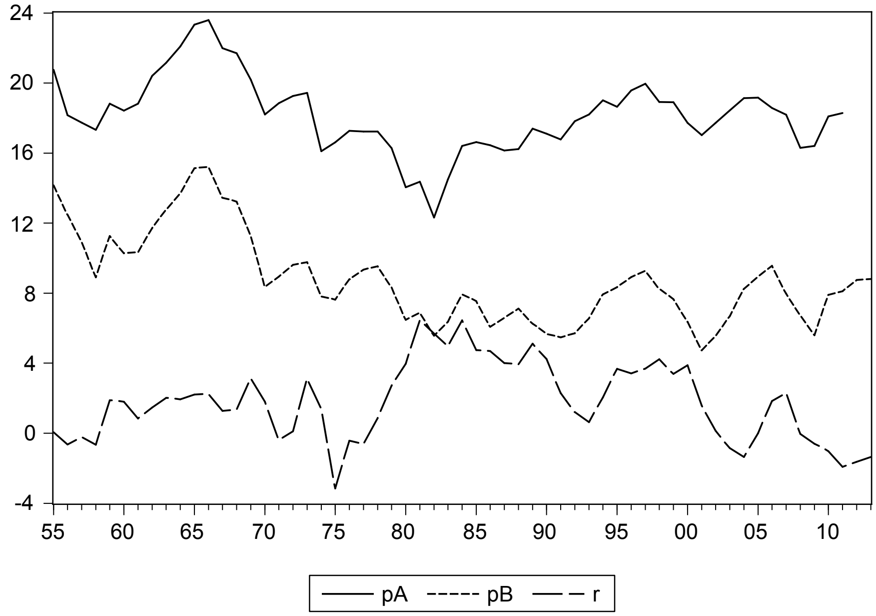

Figure 1. Rates of profit: pA=Duménil and Lévy (18) (1955-2011) and pB=nonfinancial corporate sector (1955-2013); and real rate of interest (r, 1955-2013)

Table 1. Descriptive statistics

	p_t^A *(1955-2011)*	p_t^B *(1955-2013)*	r_t *(1955-2013)*
Mean	18.17	8.77	1.87
Median	18.19	8.24	1.84
Maximum	23.59	15.21	6.45
Minimum	12.32	4.73	-3.15
Standard deviation	2.15	2.61	2.17
Skeweness	0.17	0.80	0.09
Kurtosis	3.72	2.92	2.42
Normality test[a]	0.47	0.05	0.64

Notes: [a]P-values associated with the Jarque-Bera test.

Table 2. Cross correlations of rate of profit cycles (c_t^p) with real rate of interest cycles (c_t^r) at various leads and lags[a]

	$\mathrm{Corr}(c_t^p, c_{t-2}^r)$	$\mathrm{Corr}(c_t^p, c_{t-1}^r)$	$\mathrm{Corr}(c_t^p, c_t^r)$	$\mathrm{Corr}(c_t^p, c_{t+1}^r)$	$\mathrm{Corr}(c_t^p, c_{t+2}^r)$
Using p_t^A (1955-2011)					
FD filter	-0.120	**-0.503**	0.139	0.298	-0.142
MSL[b]	0.39	**0**	0.32	0.03	0.31
HP filter	-0.299	**-0.564**	0.101	0.376	0.001
MSL[b]	0.03	**0**	0.47	0.01	0.99
BK filter	-0.224	**-0.596**	0.108	0.442	-0.071
MSL[b]	0.12	**0**	0.46	0	0.63
Bw filter	-0.236	**-0.569**	0.196	0.435	-0.099
MSL[b]	0.08	**0**	0.15	0	0.47
CF filter	-0.236	**-0.531**	0.179	0.432	-0.050
MSL[b]	0.08	**0**	0.19	0	0.72
Using p_t^B (1955-2013)					
FD filter	-0.254	**-0.393**	0.240	0.289	-0.002
MSL[b]	0.06	**0**	0.07	0.03	0.99
HP filter	-0.423	**-0.456**	0.230	0.418	0.114
MSL[b]	0	**0**	0.09	0	0.40
BK filter	-0.421	**-0.480**	0.272	0.420	0.035
MSL[b]	0	**0**	0.05	0	0.81
Bw filter	-0.372	**-0.475**	0.293	0.424	-0.003
MSL[b]	0	**0**	0.03	0	0.98
CF filter	-0.350	**-0.446**	0.311	0.410	-0.055
MSL[b]	0	**0**	0.02	0	0.68

Notes: [a]The entries are the values of the correlation coefficients. The highest values are boldly marked; [b]Marginal Significance Levels (MSL) of each filter refer to a two-tailed test.

Table 3. Estimated rate of profit equations

	FD filter	HP filter	BK filter	Bw filter	CF filter
Using p_t^A (1955-2011)					
α	0.003	-0.019	0.026	-0.015	-0.016
β	0.182	0.251**	0.207*	0.168	0.228**
γ	-0.396***	-0.454***	-0.443***	-0.447***	-0.460***
Adj. R^2	0.26	0.36	0.38	0.33	0.31
Diagnostic tests[a]	A=0.55;	A=0.87;	A=0.74;	A=0.42;	A=0.86;
	H=0.37;	H=0.99;	H=0.58;	H=0.56;	H=0.63;
	N=0.93;	N=0.45;	N=0.89;	N=0.51;	N=0.22;
	R=0.04;	R=0.10;	R=0.01;	R=0.11;	R=0.93;
Using p_t^B (1955-2013)					
α	-0.046	-0.018	0.025	-0.011	-0.005
β	0.318**	0.429***	0.374***	0.287**	0.293**
γ	-0.397***	-0.470***	-0.462***	-0.442***	-0.446***
Adj. R^2	0.25	0.38	0.37	0.27	0.25
Diagnostic tests[a]	A=0.26;	A=0.49;	A=0.37;	A=0.01;	A=0.43;
	H=0.78;	H=0.38;	H=0.98;	H=0.51;	H=0.14;
	N=0.66;	N=0.30;	N=0.52;	N=0.15;	N=0.25;
	R=0.26;	R=0.51;	R=0.08;	R=0.25;	R=0.76;

Notes: [a]The diagnostic test employed were the following: A=Autocorrelation (Breusch-Godfrey Serial Correlation LM Test); H=Heteroskedasticity (ARCH test); N=Normality (Jarque-Bera); R=Ramsey RESET test. We only report the *p*-values associated with each test.
*, ** and *** respectively denote statistical significance at the 10%, 5%, and 1% confidence levels.

Table 4. Stability tests of the rate of profit equations

	SupF[a]	AvgF[a]	ExpF[a]	Bai-Perron[b]	Hansen's L_c[a]	Elliott-Müller's qLL[c]
Using p_t^A (1955-2011)						
FD filter	0.46	0.79	0.75	10.14	0.04**	-8.21
HP filter	0.86	0.96	0.94	8.09	0.01**	-8.03
BK filter	0.83	0.92	0.90	7.61	0.02**	-7.39
Bw filter	0.86	0.96	0.95	7.45	0.01**	-7.33
CF filter	0.97	0.99	0.99	5.05	0.01**	-8.24
Using p_t^B (1955-2013)						
FD filter	0.83	0.94	0.94	4.86	0.01**	-7.14
HP filter	0.99	0.93	0.89	3.00	0.01**	-11.09
BK filter	0.71	0.76	0.69	5.68	0.01**	-14.95**
Bw filter	0.95	0.97	0.95	3.58	0.01**	-9.95
CF filter	0.97	0.99	0.99	3.40	0.01**	-10.29

Notes: [a]Only *p*-values are shown. For the SupF, AvgF and ExpF tests we show the probabilities associated with the Likelihood Ratio F-statistic calculated using Hansen (31)'s method; [b]UDMax test. Critical value: 14.23 (6); [c]Long-run variance computed with 1 lag. Critical values at 1%, 5% and 10%: -17.57, -14.32, -12.80 (21).
*, ** and *** respectively denote rejection of the null hypothesis at the 10%, 5%, and 1% confidence levels.

Table 5. Granger non-causality tests of equation (13)

	In-sample test		Out-of-sample test		
	F-statistic	*p*-value	MSPE_1[a]	MSPE_2[b]	McCracken's F-statistic[c]
Using p_t^A (1955-2011)					
FD filter	19.67	0***	1.319	1.007	$F_{1,0.1}$=1.55***
HP filter	30.57	0***	0.632	0.416	$F_{1,0.1}$=2.59***
BK filter	30.53	0***	0.454	0.176	$F_{1,0.1}$=7.91***
Bw filter	29.02	0***	0.479	0.415	$F_{1,0.1}$=0.78*
CF filter	25.22	0***	0.615	0.420	$F_{1,0.1}$=2.32***
Using p_t^B (1955-2007)					
FD filter	15.09	0***	1.481	0.600	$F_{1,0.1}$=7.34***
HP filter	25.50	0***	0.891	0.353	$F_{1,0.1}$=7.63***
BK filter	25.08	0***	0.558	0.232	$F_{1,0.1}$=7.02***
Bw filter	22.04	0***	0.476	0.269	$F_{1,0.1}$=3.85***
CF filter	19.85	0***	0.360	0.186	$F_{1,0.1}$=4.69***

Notes: [a]Mean Squared Prediction Error of the equation without c_{t-1}^r; [b]Mean Squared Prediction Error of the equation that includes c_{t-1}^r; [c]Calculated using $S = 5$ and $T = 46$ in most cases; so that $F_{1,0.1}$, where 1 denotes the excess parameter (c_{t-1}^r), and $0.1 \approx 5/46$. Critical values of $F_{1,0.1}$ at 1%, 5%, and 10% are respectively 1.480, 0.784, and 0.514 (see Table 6 in McCracken (37))
*, **, and *** respectively denote rejection of the null hypothesis at the 10%, 5%, and 1% confidence levels.

Table 6. Linear unit root tests

	ADF[a,b,c]	DF-GLS[a,b,c]	Ng-Perron[a,b,c]	KPSS[a,b,c]
p_t^A	-2.11	-2.06	-7.40	1.95***
Δp_t^A	-6.80***	-5.35***	-19.73**	0.05
p_t^B	-1.52	-1.61	-8.04	2.35***
Δp_t^B	-6.09***	-5.76***	-25.00**	0.04
r_t [d]	-2.38	-2.20**	-8.49**	1.81***
Δr_t	-7.26***	-[e]	-[e]	0.09

Notes: [a]Statistics reported: ADF and DF-GLS=t-statistic; Ng-Perron=MZa-statistic; KPSS=LM-statistic; [b]Critical values used: ADF=MacKinnon (36) one-sided p-values; DF-GLS=Table 1 of Elliott at al. (20); Ng-Perron=Table 1 of Ng and Perron (40); KPSS=Table 1 of Kwiatkowski et al. (33); [c]Δ denotes first differences of the series; [d]Period: 1955-2013. The unit root tests over the period 1955-2011 yield fairly similar results; [e]Not carried out since r_t was found to be stationary in levels at the 5% level of significance.
*, **, and *** respectively denote rejection of the null hypothesis at the 10%, 5%, and 1% confidence levels.

Table 7. Granger non-causality tests of the VAR models

Null hypothesis	χ^2 statistic	p-value
Using p_t^A *(1955-2011)*		
$r_t \nRightarrow \Delta p_t^A$	19.42	0***
$\Delta p_t^A \nRightarrow r_t$	5.09	0.08*
Using p_t^B *(1955-2013)*		
$r_t \nRightarrow \Delta p_t^B$	15.23	0***
$\Delta p_t^B \nRightarrow r_t$	3.20	0.20

*, **, and *** respectively denote rejection of the null hypothesis at the 10%, 5%, and 1% confidence levels.

Table 8. Variance decompositions from the $\Delta p_t \rightarrow r_t$ recursive VARs[a]

Forecast Horizon	Variance decomposition of Δp_t			Variance decomposition of r_t		
	F.S.E.[b]	Δp_t	r_t	F.S.E.[b]	Δp_t	r_t
Using p_t^A (1955-2011)						
1	0.96	100	0	1.36	2.75	97.25
2	1.12	74.74	25.26	1.93	9.70	90.30
3	1.12	74.59	25.41	2.10	10.65	89.35
6	1.14	73.11	26.89	2.30	10.65	89.35
Using p_t^B (1955-2013)						
1	1.05	100	0	1.37	2.69	97.31
2	1.21	77.13	22.87	1.89	8.66	91.34
3	1.23	75.19	24.81	2.09	11.04	88.96
6	1.23	75.16	24.84	2.28	12.37	87.64

Notes: [a]Percentage points are shown; [b]Forecast Standard Error.

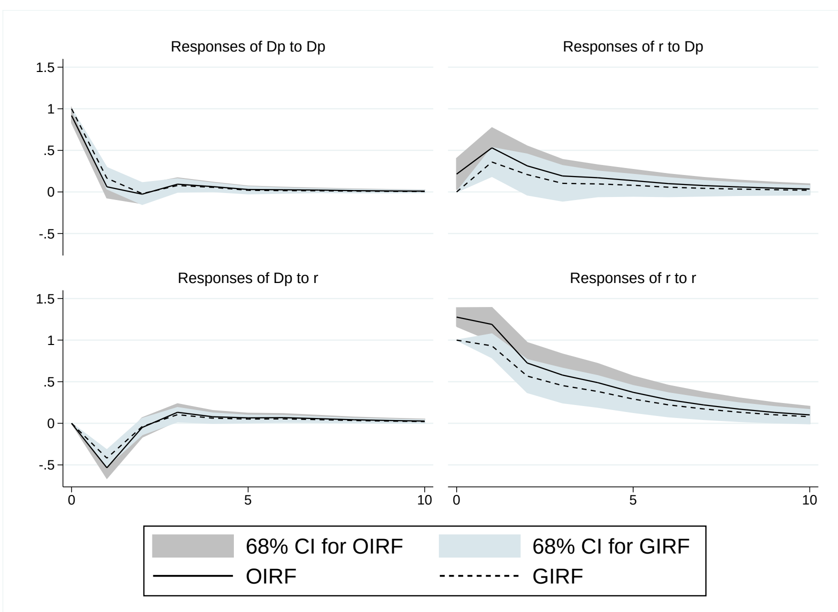

Figure 2. Orthogonal impulse responses (OIRF) from the $\Delta p_t^A \rightarrow r_t$ recursive VAR and Generalized impulse responses (GIRF) (with 68% confidence intervals (CI))

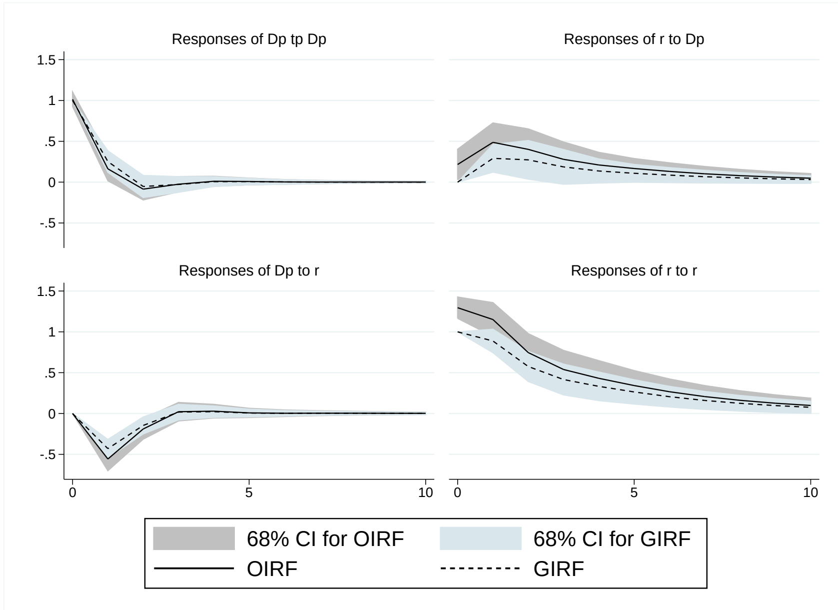

Figure 3. Orthogonal impulse responses (OIRF) from the $\Delta p_t^B \rightarrow r_t$ recursive VAR and Generalized impulse responses (GIRF) (with 68% confidence intervals (CI))

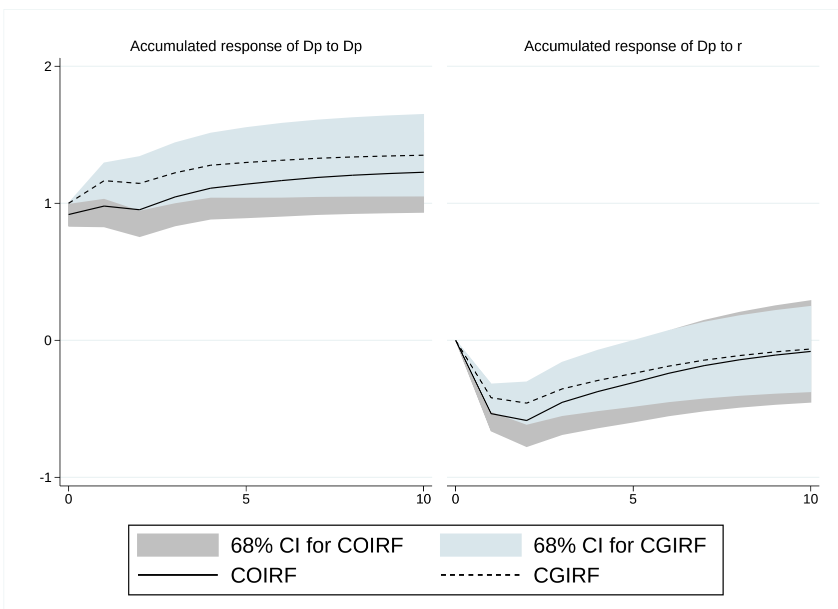

Figure 4. Cumulative orthoghonal (COIRF) and generalized (CGIRF) impulse response functions of Δp_t^A to Δp_t^A and to r_t (with 68% confidence intervals (CI))

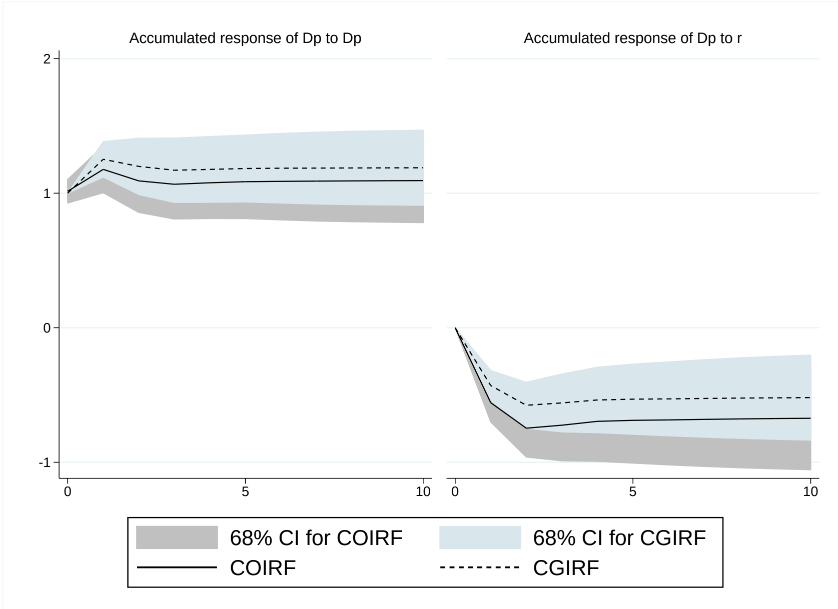

Figure 5. Cumulative orthoghonal (COIRF) and generalized (CGIRF) impulse response functions of Δp_t^B to Δp_t^B and to r_t (with 68% confidence intervals (CI))

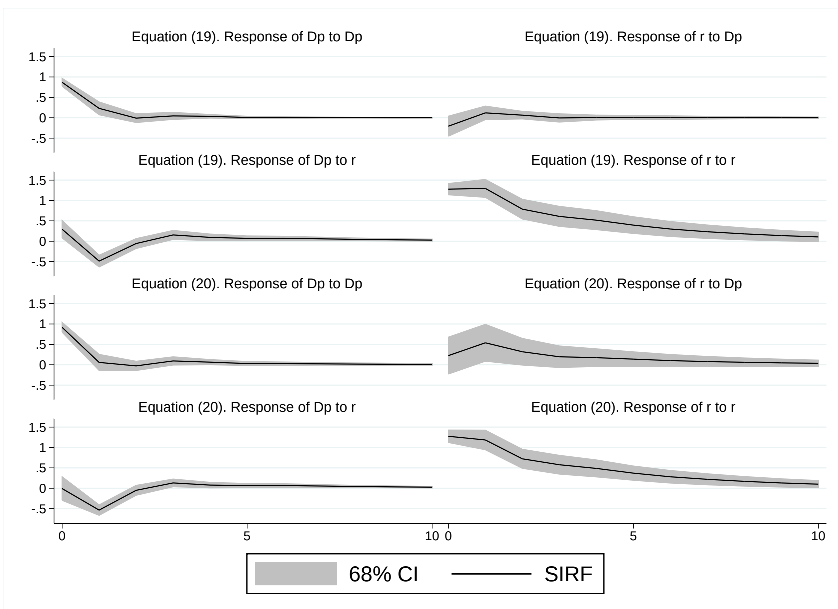

Figure 6. Δp_t^A: Structural impulse response functions (SIRF) obtained from the identifying assumptions shown in equations (19) and (20) (with 68% confidence intervals (CI))

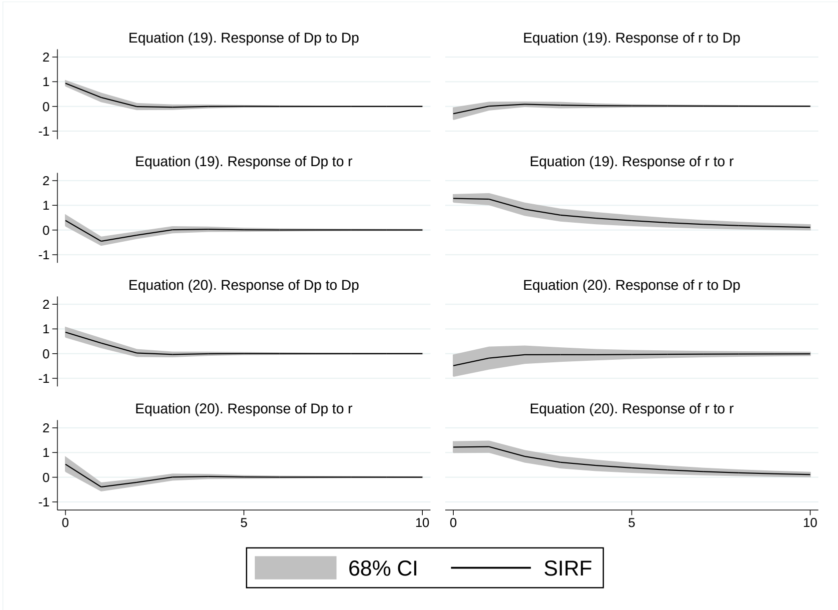

Figure 7. Δp_t^B: Structural impulse response functions (SIRF) obtained from the identifying assumptions shown in equations (19) and (20) (with 68% confidence intervals (CI))

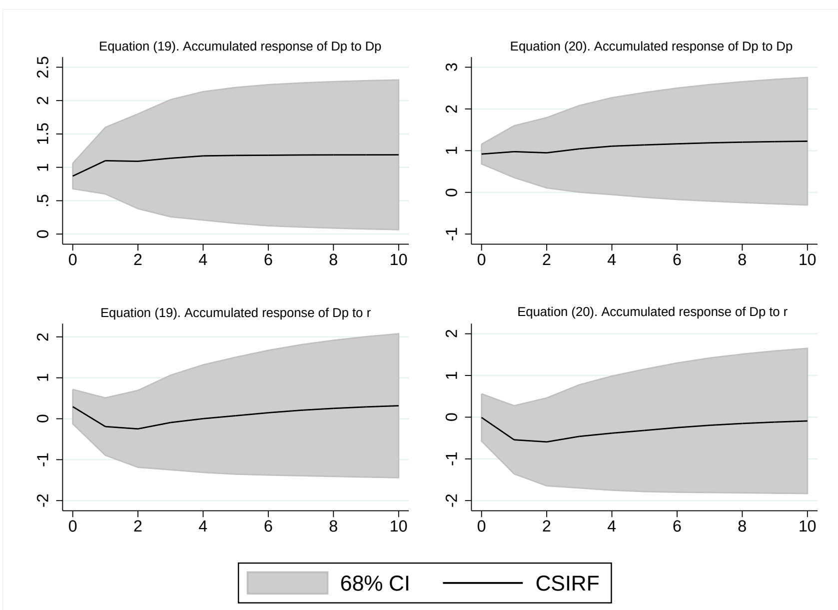

Figure 8. Cumulative structural impulse resonse functions (CSIRF) of Δp_t^A to Δp_t^A and to r_t (with 68% confidence intervals (CI))

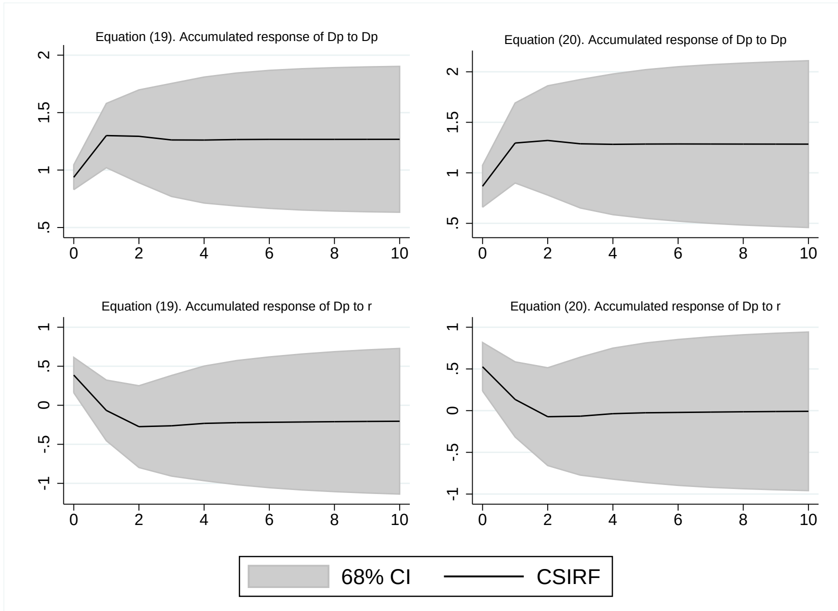

Figure 9. Cumulative structural impulse resonse functions (CSIRF) of Δp_t^B to Δp_t^B and to r_t (with 68% confidence intervals (CI))

A Stability tests employed

The SupF, AvgF and ExpF tests are build on the traditional exogenous structural break tests, but are constructed for unknown break points (τ_b) and allow to determine the most likely position of τ_b:

$$\mathrm{SupF} = \max_{\tau_1 \leq \tau_b \leq \tau_2} \mathrm{F}(\tau_b) \tag{A.1}$$

$$\mathrm{AvgF} = \frac{1}{k+1} \sum_{\tau_b=\tau_1}^{\tau_2} \mathrm{F}(\tau_b) \tag{A.2}$$

$$\mathrm{ExpF} = \ln\left(\frac{1}{k+1} \sum_{\tau_b=\tau_1}^{\tau_2} \exp\left(\frac{1}{2}\mathrm{F}(\tau_b)\right)\right) \tag{A.3}$$

where τ_b denotes the date of the structural change which lies between τ_1 and τ_2; and k is the number of regressors in the equation.

Bai and Perron (4) describe global optimization procedures for identifying the multiple breaks which minimize the sums-of-squared residuals in a regression model. Regarding equation (13), we have the following:

$$\begin{aligned} c_t^p &= \mathbf{X_t'}\beta_{\mathbf{j}} + \eta_t \\ t &= T_{j-1}+1, ..., T_j \\ j &= 1, ..., v+1 \end{aligned} \tag{A.4}$$

where $\mathbf{X_t}$ is the vector of covariates with coefficients β; and we specify T_j periods with v potential breaks that produce $v+1$ regimes. Both the break dates $(T_1, ..., T_v)$ and the unknown regression coefficients $(\beta_1, ..., \beta_v)$ are explicitly treated as unknown and are simultaneously estimated; and the least squares estimates of β and v are obtained by minimizing the sum of squared residuals issued from the estimation of the v regressions ($S_t(T_1,...,T_v)$):

$$\underset{T_1,...,T_v}{\arg\min}\, S_t(T_1,...,T_v) = \sum_{j=1}^{v+1} \sum_{t=T_{j-1}+1}^{T_j} \left(c_t^p - \mathbf{X_t'}\beta_\mathbf{j}\right)^2 \tag{A.5}$$

The global v-break optimizers are the set of breakpoints and corresponding coefficient estimates that minimize sum-of-squares across all possible sets of v-break partitions. These global breakpoint estimates can be used as the basis for several breakpoint tests, and we employed an F-statistic in order to test for equality of the $\beta_\mathbf{j}$ coefficients across multiple regimes.

Hansen (30)'s L_c test statistic is essentially an average of the squared cumulative sums of first order conditions, in which the null hypothesis of stability is rejected for large values of L_c. The joint stability test statistic is:

$$L_c = \frac{1}{n}\sum_{t=1}^{n} \mathbf{R_t'}\mathbf{V^{-1}}\mathbf{R_t} \tag{A.6}$$

where in this case: $t = 1,2,...,n$; $\mathbf{V}$=$\mathbf{f_t f_t'}$; $\mathbf{f_t} = (f_{1t},...,f_{k+1,t})$, where: $f_{it} = \begin{cases} x_{it}\widehat{\eta}_t, & i = 1,...,k \\ \widehat{\eta}_t^{\,2} - \widehat{\sigma}^2, & i = k+1 \end{cases}$, and the different x_{it} are the elements that compose the vector $\mathbf{X_t}$; and $\mathbf{R_t} = (R_{1t},...,R_{k+1,t})$, where $R_{in} = \sum_{t=1}^{n} f_{it}$.

Finally, Elliott and Müller (21)'s quasi-local level (qLL) test is asymptotically point-optimal for a broad set of breaking processes, so that it is not necessary to make specific assumptions about the particular process governing the time variation of coefficients. It also has a number of advantages: 1) it does not require computations for each possible combination of break dates; 2) it requires no trimming of the data; and 3) it has superior size control in small samples than other popular tests (particularly when the disturbances are heteroskedastic). The null hypothesis of joint parameter stability is rejected if the test statistic is smaller (more negative) than the critical values shown in Elliott and Müller (21).

B Individual and joint diagnostic tests of the VAR models

Table B1. Individual and joint misspecification tests over the VAR(2) model using Δp_t^A

	Autocorrelation		Heteroskedasticity		Normality	
Individual tests[a]						
Equation	F-statistic	*p*-value	F-statistic	*p*-value	Statistic	*p*-value
Δp_t^A	1.00	0.37	1.58	0.21	0.14	0.93
r_t	0.74	0.48	0.42	0.52	0.18	0.91
Joint tests[b]						
	Statistic	*p*-value	χ^2 statistic	*p*-value	Statistic	*p*-value
	2.79	0.59	53.18	0.12	0.50	0.97

Notes: [a]Tests employed: Serial correlation=Breusch-Godfrey LM; Heteroskecasticity=ARCH; Normality=Jarque-Bera; [b]Tests employed: Serial correlation=LM; Heteroskedasticity=White (including cross terms); Normality=Cholesky of covariance (Lutkepohl).

Table B2. Individual and joint misspecification tests over the VAR(2) model using Δp_t^B

	Autocorrelation		Heteroskedasticity		Normality	
Individual tests[a]						
Equation	F-statistic	*p*-value	F-statistic	*p*-value	Statistic	*p*-value
Δp_t^B	1.39	0.26	1.13	0.29	0.40	0.82
r_t	0.41	0.67	0.93	0.34	0.51	0.78
Joint tests[b]						
	Statistic	*p*-value	χ^2 statistic	*p*-value	Statistic	*p*-value
	3.02	0.56	55.99	0.07	0.52	0.97

Notes: [a]Tests employed: Serial correlation=Breusch-Godfrey LM; Heteroskecasticity=ARCH; Normality=Jarque-Bera; [b]Tests employed: Serial correlation=LM; Heteroskedasticity=White (including cross terms); Normality=Cholesky of covariance (Lutkepohl).

Table B3. Stability tests over the VAR(2) model

Equation	Hansen's L_c		Elliott-Müller's qLL statistic[a]
	L_c statistic	p-value	
Using Δp_t^A			
Δp_t^A	0.98	0.04**	-18.89
r_t	2.37	0.01**	-21.25
Using Δp_t^B			
Δp_t^B	1.83	0.01**	-18.34
r_t	2.45	0.01**	-22.34

Notes: [a]Long-run variance computed with 1 lags. Critical values at 1%, 5% and 10%: -29.18, -25.28, -23.37 (21)
*, **, and *** respectively denote rejection of the null hypothesis at the 10%, 5%, and 1% confidence levels.

C Impulse response functions from the VAR models following the opposite order

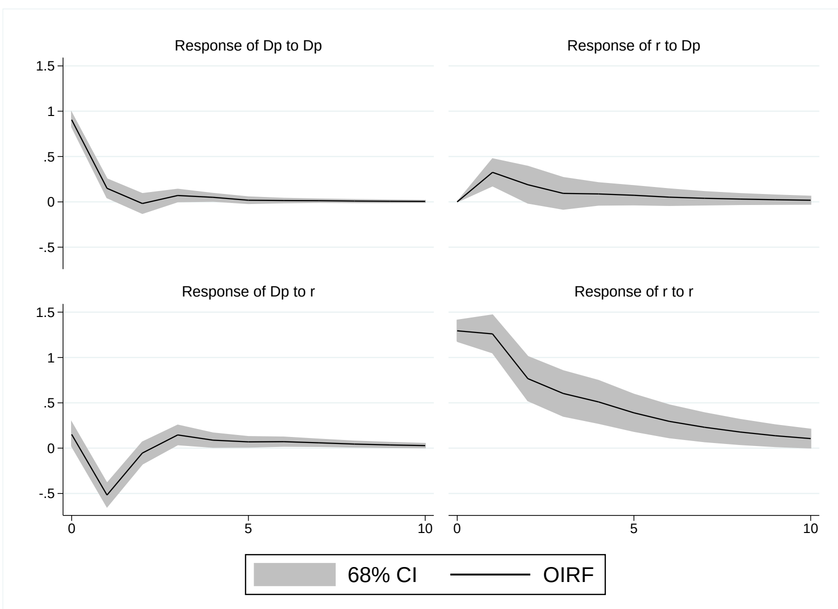

Figure C1. Orthogonal impulse responses (OIRF) from the $r_t \rightarrow \Delta p_t^A$ recursive VAR (with 68% confidence intervals (CI))

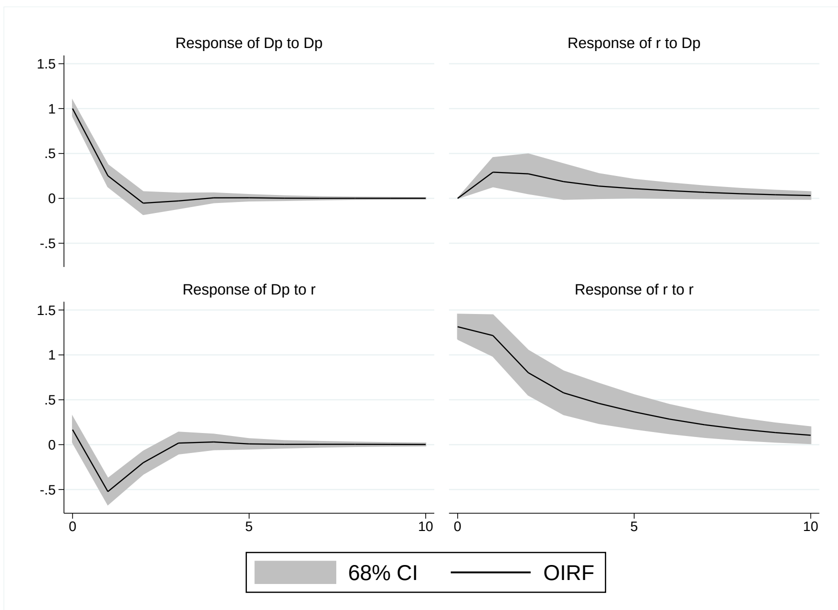

Figure C2. Orthogonal impulse responses (OIRF) from the $r_t \to \Delta p_t^B$ recursive VAR (with 68% confidence intervals (CI))