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Do building permits act as a leading indicator of Italy short-term production in construction?

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Index of production in construction and building permits are two indicators used to describe the short-term evolution of the construction sector. In particular, the former measures the level of activity in terms of the sector output, whereas the latter are meant to anticipate production in construction in the very near future, as they represent the administrative applications to start building activity. Nevertheless, for a number of reasons to be detected, building permits do not always act as a leading indicator of the construction sector short-term performance. To investigate whether there are any leading-lagging relations between these two variables, a descriptive analysis based on cross-correlations has been preliminarily carried out and then supplemented by the application of a VAR (Vector Autoregressive) model, used to analyse Granger causality within a cointegrated system of the two variables.

keywords: Building permits, Construction production, Granger causality, Cointegration.

1 Introduction

Among the Principal European Economic Indicators (PEEIs), the key macroeconomic short-term statistics used for monitoring the macroeconomic situation of the euro area, the index of production in construction (IPC) and building permits (BP) are the two

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The opinions expressed do not necessarily reflect the view of the National Institute of Statistics (Istat). Even though this paper is the outcome of a join effort, sections 2, 3, 4.1 and 4.2 are attributable to C. Corea, whereas sections 4, 4.3 and 4.4 to G. Bruno.

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indicators focused on the construction sector. Due to their partial coverage of the total construction production - neither civil engineering works nor maintenance activity are covered - and to the lag between the moment when the permission is issued and the time when a building is constructed, BP might not always act as a leading indicator of the production, as it is expected. Using quarterly data for the period 2000:Q1-2016:Q3, in this paper the empirical issue concerning the lagging-leading relation between IPC and BP has been investigated by means of a Granger causality test, in a time series analytical framework. The characteristics of the two time series have been previously analysed, to identify possible unit roots and the presence of cointegration between them. Before applying these more advanced statistical tools, a descriptive analysis, mainly based on cross-correlations, provided first hints on the time series cyclical behaviour and their co-movements.

2 Variables

Apart from considering the different phenomenon that production in construction and building permits are intended to measure, particular attention should be paid to the underlying concepts and definitions and to their different frequency, also to point out all those aspects affecting a joint analysis of these two short-term indicators.

The first of them measures the level of activity in the construction sector (with respect to the base year), whereas building permits, measured in terms of the floor for which they are requested and granted, are meant to anticipate the production activity in the near future.

It can be useful to remind that the index of production in construction (base year 2010) is compiled and released every month using an indirect method[1] that allows to measure, in terms of volume, the evolution of the production in the sector using input data (hours worked, intermediate input and gross fixed capital). The production volume is considered a reasonable approximation of the value added at constant prices, the variable that the STS European Regulation[2] indicates as the most suitable to represent the short-term evolution of the whole construction sector output, covering all building construction (residential and non-residential), civil engineering works and maintenance activity.

As far as BP, it is a volume variable, released on a quarterly basis and measured in terms of absolute figures, but here transformed into an index number by referencing it to a base year. This indicator has to be intended as the number of square meters of usable[3]

[1] A production function of the construction sector is estimated for the base year using 2010 Structural Business Statistics (SBS) data. The estimates of the production function coefficients represent the weights assigned to the input data to estimate the output. For the current updating of the index, input data are taken from different sources: worked hours from administrative sources (register of building workers' welfare funds), turnover from Istat current survey on monthly industrial turnover and monthly estimates of capital stock derived from annual National Accounts data.

[2] EU Regulation n.1165/98 and emendation n.1158/05.

[3] The usable floor area of a building is measured within its external walls, excluding construction areas (for example areas of demarcation components, supports, columns, pillars, shafts, chimneys),

floor area for new residential buildings, whereas for non-residential buildings the number of square meters of total floor area is considered. So, strictly speaking, the two variables could not be summed up to have an overall BP indicator, as the underlying definition of floor area is not the same: a concept of usable floor area is used for the residential sector, instead of an idea of gross floor area for the non-residential one. However, when being interested only in describing the overall dynamic of the building permits and comparing it with the evolution of the actual construction activity, despite the previous caveats, a proxy of the total building permits (hereinafter TBP) has been obtained by summing up the two variables.

In comparing BP and IPC cyclical components, it should also be underlined that, while production in construction is referred to the whole production activity of the construction sector, BP covers only building construction, both residential and non-residential, excluding the civil engineering and maintenance works.

Therefore, if a TBP indicator is used, it is only an approximation of the overall floor area for which licenses to build have been granted; if only residential construction building permits (hereinafter RBP) are considered, the field of observation is even more restricted when compared to IPC domain.

In addition, it should be noticed that, on one hand, not all the granted permits lead to real building works (not all projects end up being carried out) and, on the other hand, construction activity can last long, making it difficult to connect the output to the obtained licenses. So, building permits presumably covers a relevant part of the IPC field of observation, but surely not the entire production.

As it affects the time series pattern and the dynamic relations between them, another aspect to be considered is that IPC estimates have to be converted to a quarterly frequency to compare them with building permits data that are surveyed every month, but compiled and released as final estimates only on a quarterly basis. In this respect, the transformation of the production data probably affects their original monthly pattern.

Finally, the use of BP data can also be affected by changes in legislation or by the level of efficiency in the public administration. In fact, the transmission timing to the public authorities in charge of collecting BP data or the content of the information itself can change over time according to the legislative modifications. The quality of the final BP estimates also depends on the readiness and the accuracy in collecting data and transmitting them to the National Institute of Statistics.

functional areas for ancillary use (for example areas occupied by heating and air-conditioning installations, or by power generators), thoroughfares (for example areas of stairwells, lifts, escalators). The part of the overall useful area of a building used for residential purposes includes the area used for kitchens, living rooms, bedrooms and ancillary rooms, cellars and common rooms used by the owners of the residential units.

3 Preliminary descriptive analysis

To compare the IPC and BP cyclical components, the first step consists in detrending the time series[4] using the Hodrick-Prescott filter (Hodrick and Prescott, 1997)[5]. Despite some known drawbacks (e.g. the choice of the smoothing parameter λ), this method to extract the cyclical component is widely used in many empirical analysis, to remove the low-frequency component, while retaining the major cyclical features of the seasonally adjusted series

In general, a detrending method is not neutral with respect to the results obtained (Canova, 1998). In the specific case of the HP filter, in addition to the selection of the λ value, one of the most significant disadvantages is that this filter can produce a spurious cyclical behaviour (Harvey and Jaeger, 1993) as well as spurious dynamic relations (Hamilton, 2017).

On the other hand Canova (1999), in an extensive study, shows that HP and the band-pass (BP) filter – like the one proposed by Baxter and King (1999) – are able to generate "cycles capturing the essence of what the community perceives as business cycle fluctuations"[6]. This is the reason why the HP filter has been used here.

A graphical inspection (Figure 1) of the extracted cyclical components shows the building permits greater volatility, a behaviour undoubtedly confirmed by the autocorrelation functions, showing that IPC is more persistent than the BP one, either considering residential building permits or the proxy of the total building permits.

Figure 2 shows the lower persistence of residential building permits; the same applies to total building permits whose autocorrelation function is not reported here.

All these evidences represent, after all, an expected result, considering the different nature of the two observed series: a production variable versus an indicator of administrative applications to start building activity.

In a bivariate and descriptive approach, the cross-correlogram, useful to represent the co-movements between the two considered series, can also provide some indications on their possible mutual predicting attitude. In the case under study, the cross-correlation

[4] All the data used are log-transformed.

[5] Assuming that a time series y_t can be decomposed into a trend component τ_t, a cyclical component c_t and a residual component ε_t, the Hodrick-Prescott filter is a smoothing method to obtain an estimate of the cycle (that is to remove/identify the trend component). For a sample of T observations, the trend term τ_t is estimated by solving the constrained minimization problem:

$$\min_{(\tau_1,\tau_2,\ldots,\tau_T)} \left\{ \sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} \left[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}) \right]^2 \right\}$$

where λ is a positive smoothing parameter which penalizes the variability in the trend component. The first term represents the sum of the squared deviations $y_t - \tau_t$, whereas the second one regulate variations in the growth rate of the trend component, being a multiple λ of the sum of the squares of the trend component's second differences. As λ approaches 0, less regular estimates of τ_t are admitted (closer to the original data y_t), whereas as λ increases, the solution τ_t will be characterized by very low variations in the growth rate, namely, it will be an almost linear trend. The default parameter λ value is set at 1600 for quarterly series.

[6] The results obtained using the BP filter are not qualitatively different from those presented in the HP case and are available upon request.

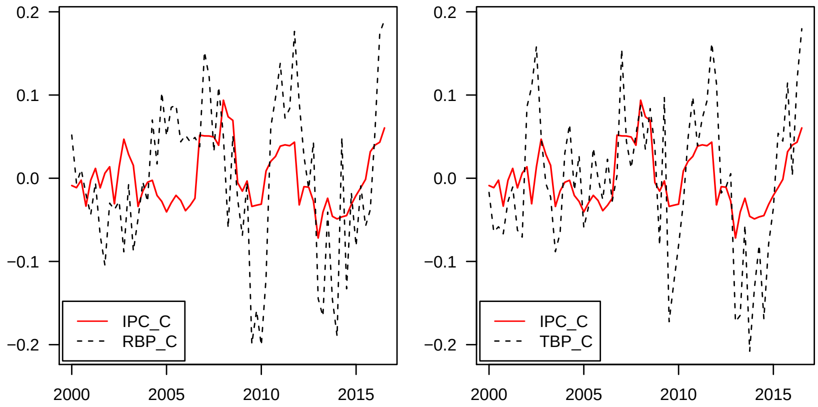

Figure 1: Index of production in construction and building permits (RBP and TBP) cyclical components

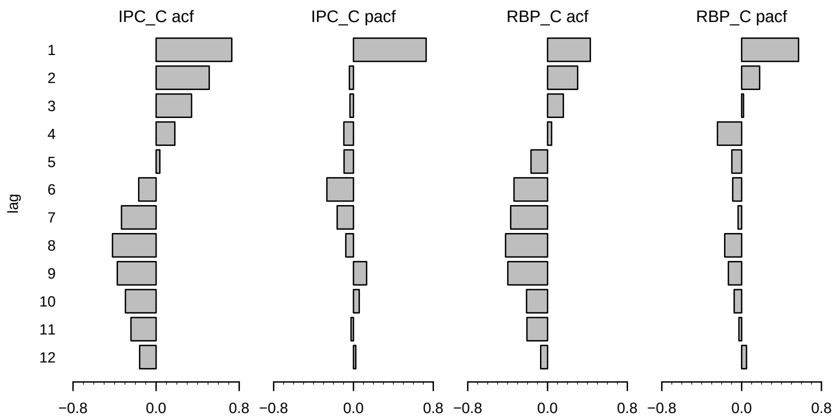

Figure 2: IPC and residential BP cyclical components autocorrelation function

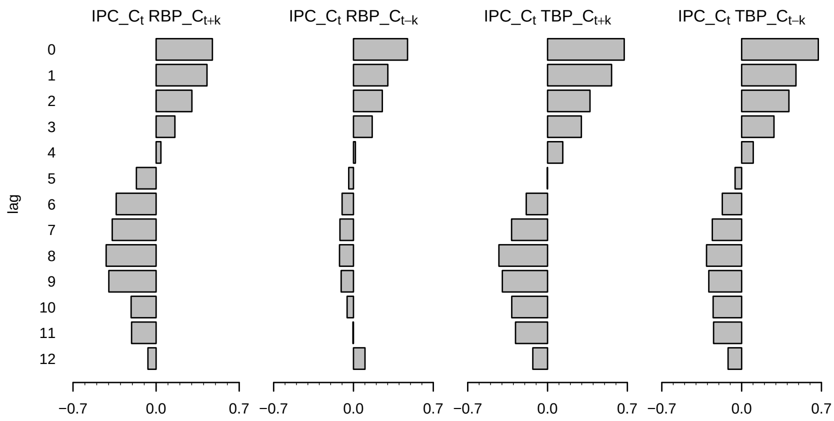

Figure 3: Cross-correlation between BP (residential and total) and IPC cyclical components

coefficients (Figure 3) reveal that the two indicators are coincident, overturning the expectation that building permits can be a leading indicator for production in construction. However, to exclude or to prove any leading-lagging relation between them, more sophisticated statistical techniques will be applied in the next section. However, it is worth noticing that the cross-correlation is higher when considering TBP.

4 A time series analysis framework

A deeper analysis of the relationships between IPC and BP can be performed by applying a more formal time series analysis framework. Here we use the concept of Granger causality (Granger, 1969), which arises quite naturally in this context, because it is defined precisely in terms of forecasting improvement for a variable determined by the use of another variable. The basic idea of the Granger causality is that the past values of a variable, e.g. BP, have a predictive power about the current value of another variable, say IPC. At the same time, causation can run also in the opposite direction.

More formally, a variable x_t is said not to cause (in Granger sense) y_t if:

$$D(y_t|y_{t-1}, y_{t-2}, \cdots, x_{t-1}, x_{t-2}\cdots) = D(y_t|y_{t-1}, y_{t-2})$$

where $D(\cdot)$ is the forecast density function. We denote causality of x_t over y_t with $x_t \to y_t$.

Note that Granger causality of x_t towards y_t neither implies nor it is implied by the reverse relation; therefore we could have that $x_t \to y_t$ but $y_t \not\to x_t$, and vice-versa. Moreover we could also have bi-directional causality (a *feedback* system) or no causality at all as well.

The concept of Granger causality has been criticized in many respects, first of all because of the possible misunderstanding arising from the very term causality. Actually, counterexamples can be constructed where a cause-effect relation is not revealed by the

Granger definition and vice-versa. In our setting this is a minor flaw, because we are mainly interested in the forecasting content of a variable for another one rather than true cause-effect relations, which is the essential content of Granger causality. Nevertheless, other critical issues linked to Granger causality are still present in this framework. Namely the inconsistencies which can arise from finding causality in a model and its actual existence in the data generating process (DGP) (Hendry, 1997). This point is also related to the fact that the results depend on the system dimension and it is obviously implausible that a system with a limited number of variables contains all the relevant information.

Indeed, in this case, most of the previous points are not so critical, given that we are mainly interested just in the forecasting ability of BP over IPC. The only remaining limitation over this point is due to the fact that Granger causality is usually tested with reference to a linear model, so absence of causality emerging from such tests would not exclude a more general forecasting capability of BP in a non-linear setting (Qiao et al., 2009).

A further complication, however, arises from the possible non-stationarity of the variables involved. Indeed, non-stationarity in mean is quite common in macroeconomic time series, which are often found to contain a so called *unit root*. As we will see, this is the case also for the variables considered here. Moreover, whenever we estimate relations based on non-stationary variables we should also care about possible cointegration of these variables. In the present context this is relevant as we know that cointegration implies always Granger causality in at least one direction (Engle and Granger, 1987). A similar problem, although in a different context, is dealt with by Al Barghouthi et al. (2016), where also causality in presence of cointegration is explored.

4.1 Unit root properties

The Augmented Dickey Fuller (ADF) approach is one of the most used test to verify the null hypothesis of non-stationarity against the alternative of stationarity. It is an extension of the Dickey-Fuller test based on a parametric correction for residual correlation in the test regression. Assuming that the y_t follows an $AR(p)$ process, the test allows to verify the null hypothesis that $\rho = 1$:

$$\Delta y_t = \alpha + \gamma t + (\rho - 1) y_{t-1} + \beta_1 \Delta y_{t-1} + \cdots + \beta_p \Delta y_{t-p} + \varepsilon_t \tag{1}$$

The results reported in Table 1 show that IPC and BP (both residential and total building permits) are non-stationary, as the null hypothesis that a unit root is present cannot be rejected.

The presence of a unit root has been confirmed by the KPSS (Kwiatkowski et al., 1992) test (Table 2), whose null hypothesis is the stationarity.

The same unit root tests run on the differenced series has excluded the presence of multiple roots, i.e. an integration order higher than 1, for all the considered variables.

As we have found quite a sharp evidence that all the series considered here do have a unit root, we proceed to verify the cointegration hypothesis. We remind that cointegration implies causality in at least one direction. Also in this case we use more than

Table 1: ADF unit root test on IPC, RBP and TBP (a)

Null hypothesis	IPC has a unit root		RBP has a unit root		TBP has a unit root	
	t-statistic	p-value	t-statistic	p-value	t-statistic	p-value
	-1.6551	0.76	-1.8217	0.68	-2.2785	0.44

(a) Regression test with a constant and a linear trend. Lag chosen by SIC criterion. MacKinnon (1996) one-sided p-values.

Table 2: KPSS stationarity test on IPC, RBP and TBP (a)

Null hypothesis:	IPC is stationary	RBP is stationary	TBP is stationary
test statistic	0.2600	0.2455	0.2373
critical values (b) 1%	0.2160	0.2160	0.2160
5%	0.1460	0.1460	0.1460
10%	0.1190	0.1190	0.1190

(a) Regression with a constant and a linear trend, NW automatic bandwidth selection using Bartlett kernel.
(b) Kwiatkowski et al. (1992)

one procedure to test the hypothesis of interest, in order to have more robust results. In particular we will rely both on single equation tests and on a system approach.

4.2 Single equation test

The most basic approach to carry out a single equation test is by means of the two-step procedure proposed by Engle and Granger (1987). This amounts to test for stationarity of the residuals of the regression between the levels of the two variables considered. In case of cointegration, in fact, the residuals should be stationary. This can be verified by means of the ADF test using, however, a different set of critical values to take into account that residuals from an estimated relation are used. The Engle-Granger procedure resorts to an ADF test is to verify the null hypothesis of non stationarity of the residuals of the cointegration regression between the two considered variables. A p-lagged augmented regression is therefore estimated in the form:

$$\Delta\hat{u}_t = (\rho - 1)\hat{u}_{t-1} + \sum_{j=1}^{p} \delta_j \Delta\hat{u}_{t-j} + v_t \tag{2}$$

Here, the null hypothesis to be tested is $H_0 : \rho = 1$. The results of this test do not allow us to refuse the null of no cointegration, as showed in Table 3

Although the procedure proposed by Engle and Granger is consistent and it is appealing because of its simplicity, it is well known that is has some drawbacks. Alternative single equation procedures have been proposed, such as those of Phillips and Hansen (1990); Stock and Watson (1993); Vogelsang and Wagner (2014).

Table 3: EG cointegration test on IPC and BP (RBP and TBP) (a)

Null hypothesis: IPC and RBP are not cointegrated		
	t-statistic	p-value
Engle-Granger τ statistic	-2.2398	0.41
Engle-Granger z statistic	-7.0099	0.55
Null hypothesis: IPC and TBP are not cointegrated		
	t-statistic	p-value
Engle-Granger τ statistic	-1.9018	0.58
Engle-Granger z statistic	-4.9644	0.73

(a) Cointegrating regression with a constant. Lag chosen by SIC criterion. MacKinnon (1996) one-sided p-values.

Table 4: Fully modified OLS cointegration test on IPC and BP (RBP and TBP)

	Dependent variable: IPC			
Regressor	coefficients	std.error	t-stat	p-value
RBP	0.2849	0.0243	11.71	0.00
C	3.1773	0.1157	27.45	0.00
	Dependent variable: IPC			
Regressor	coefficients	std.error	t-stat	p-value
TBP	0.3007	0.0315	9.53	0.00
C	3.1054	0.1493	20.97	0.00

In Table 4 we provide the results of the Fully Modified OLS estimator proposed by Phillips and Hansen (1990), where the estimated regression coefficient is significantly different from zero, suggesting, in this case, the presence of a long-run relation between the levels of the variables, i.e. the presence of cointegration[7].

In both cases, IPC is the dependent variable, whereas BP is the regressor (RBP in the first case, TBP in the second one)[8].

[7] Similar results, confirming the presence of cointegration, are also obtained with the tests proposed by Stock and Watson (1993) and Vogelsang and Wagner (2014) and are available from the authors upon request.

[8] Actually, the cointegrating regression can be also specified using IPC as dependent variable and BP as the explanatory one. However, the results presented here are robust to the choice of the normalizing variable.

Table 5: Johansen trace test of cointegration between IPC and RBP

Null hypothesis	Test value	Critical values		
		10%	5%	1%
$H_0 : r = 0, H_1 : r > 0$	22.05	17.85	19.96	24.60
$H_0 : r = 1, H_1 : r = 2$	3.52	7.52	9.24	12.97

Table 6: Johansen maximal eigenvalue test of cointegration between IPC and RBP

Null hypothesis	Test value	Critical values		
		10%	5%	1%
$H_0 : r = 0, H_1 : r = 1$	18.53	13.75	15.67	20.20
$H_0 : r = 1, H_1 : r = 2$	3.52	7.52	9.24	12.97

4.3 A system approach: the Johansen procedure

The procedure proposed by Johansen (1988, 1991) considers a different approach. It starts from a vector y_t containing the variables of interest modelled as a vector autoregressive (VAR) model of order p, and considers the equivalent vector error correction (VECM) representation:

$$\Delta y_t = \nu_0 + \Pi y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta y_{t-j} + \varepsilon_t \tag{3}$$

The VECM representation has the appealing feature of separating the parameters describing the long-run dynamics (Π) from those representing the short-run one (Γ_j).

In case of cointegration among the variables the matrix Π is of reduced rank, and the procedure proposed by Johansen tests the rank of such a matrix. In particular, if the dimension of Π is $q \times q$ and it has rank $r < q$, then r is the number of linear independent cointegration relationships. When $r = 0$ the variables are not cointegrated.

Johansen actually proposes two test for the number of cointegrated vectors: the *maximum eigenvalue test* where the null hypothesis is that there are r cointegrated vectors (for $r = 0, 1, .., q - 1$) against the alternative that there are $r + 1$ cointegrating vectors, and the *trace test*, where the null hypothesis is as before and the alternative is that there are q cointegrated vectors.

As in the considered system there are two variables, there is cointegration if and only if $r(\Pi) = 1$. The only deterministic variable is a constant term which is restricted into the cointegrating vector.

The results in both Table 5 and Table 6 confirm the presence of cointegration between IPC and RBP at conventional confidence levels. These results, even though less sharply, also hold between IPC and TBP. Therefore, from all the previous analysis we can con-

Table 7: Granger causality tests on IPC and RBP

Null hypothesis	test statistic	distribution	p-value
IPC does not cause RBP	5.77	$F_{1,120}$	0.00
RBP does not cause IPC	8.55	$F_{1,120}$	0.00

fidently conclude that IPC and RBP (TBP) are cointegrated, implying the presence of Granger causality in at least one direction.

4.4 Granger causality test and impulse response function

One of the most applied tests for causality is in the framework of a VAR system.

Causality, in fact, implies simple zero restrictions on some coefficients of the VAR, thus allowing an easy implementation of the test. When dealing with integrated variables, however, some problems arise, due to the possible non-standard distribution of the test. A general treatment in this case is provided by Toda and Yamamoto (1995), who define a modification of the original test. Although it is simple, this modification requires the estimation of a VAR of larger order, thus lowering the power of the test.

However, in the particular case of a cointegrated VAR with two variables both I(1) a result from Lütkepohl and Reimers (1992) states that the usual Granger causality tests are applicable, as they have the usual distribution used in the stationary case. Given the findings in subsections 4.2 and 4.3 this result is indeed applicable in the present case; therefore the usual Granger causality test (as in the stationary case) will be used here.

The results, which are shown in Table 7, reveal bi-directional causality, thus suggesting the presence of feedback effects between IPC and RBP. Analogous results hold for TBP. The conclusion is that while both BP variables have a forecasting content for IPC, the converse is also true.

The consequence in modelling terms is that, at least in this particular case, the use of BP data to forecast IPC should be done in a framework which allows for feedback effects, like a VAR model, while a single equation autoregressive distributed lag (ARDL) model, usually applied in a pure leading indicator context, would be inadequate to capture these features of the data.

Moreover, the estimated VAR model allow us to determine the sign of the effect of a shock on a variable on the other variable of the system. This can be easily carried out means of the so called impulse response function.

In particular, in this case (Figure 4), a positive unit shock on TBP (or RBP) determines a positive effect to IPC in the long run while, on the contrary, a positive unit shock on IPC will be reflected in a negative long run effect on TBP (RBP). This can be interpreted as the outcome that as a positive shock on production leads to an increase in buildings stock, this will be subsequently reflected in a lower demand of new permits.

The same results, from a qualitative point of view are obtained using orthogonalized impulse responses, independently from the ordering of the variables.

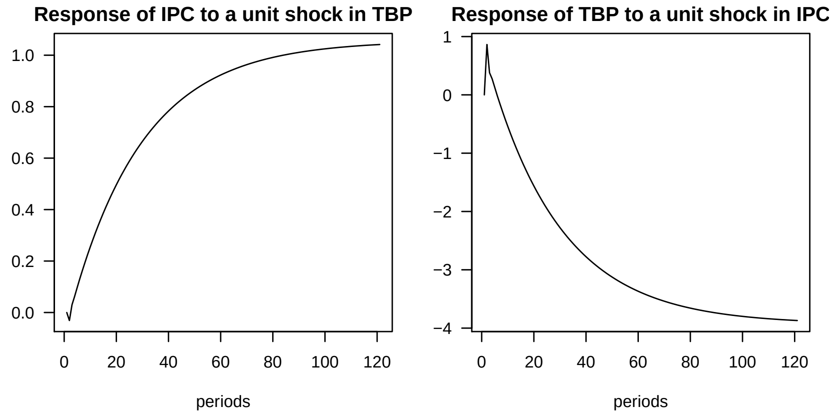

Figure 4: Impulse response functions of IPC wrt TBP and vice versa

5 Conclusions

The results of the paper allow us to conclude with a reasonable confidence that IPC and BP series are significantly connected from a time series point of view. In particular, they both present a unit root and are cointegrated. Moreover, causality in the Granger sense is likely to be present in both directions. The consequences from a practitioner point of view is that in order to use BP for helping forecasting IPC it would be wise using a system approach, like a VAR, which allows for feedback between the two variables, rather than a typical leading indicator single equation model where IPC would be the dependent variable. In this sense, it is not possible to conclude that BP is a leading indicator of IPC.

The cross-correlation coefficients considered to approach the issue from a descriptive show that IPC and BP seem to be coincident indicators.

In general, the results of the preliminary analysis lead to conclude that, apart from the cross-correlations, there are no substantial differences in using residential or total BP. The same applies for the cointegration and causality tests.

The different nature of the two variables (actual production versus an administrative license granted to undertake building activity), their different frequency and their different fields of observation surely affect their dynamic relations, requiring further investigations about how these differences influence the results here exposed.

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