Identifying Noise Shocks: a VAR with Data Revisions*

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Abstract

We set out to show how the use of different vintages of data delivers a simple identification strategy that allows to study the impact of data imperfections on the business cycle. Our findings suggest that an erroneous report of output growth numbers delivers a persistent and hump-shaped response of real output and unemployment. When we include investment in our estimation we find that it displays a significant response to noise shocks too, while the responses of output growth and unemployment are still significant.

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1 Introduction

The growing popularity of dispersed-information DSGE's make the empirical study of noise shocks more relevant than ever as an instrument to assess the relevance of models.

While the statistical properties of data revisions have been widely documented (see Makinw and Shapiro (1986) and Arouba (2008) among others), their economic implications for the business cycle have not received much attention.

Our aim is to cast some light on this, with a simple econometric model. We assume that early vintages of data are a noisy (or at least preliminary) version of the final release, which we assume to correspond to the truth. While the ongoing data revision processes might legitimately raise doubts on the latter assumption, we nonetheless see it as an extremely useful benchmark as basic econometric analysis would simply assume the latest release to be the true one, simply disregarding past as well as future revisions.

We do not make any economic assumption although one is implicit. Our analysis would not make sense in a world (or model) in which true values for the relevant economic variables are known with certainty immediately or at a very short lag. Noise shocks have no reason to produce any economic effect once all the information is revealed. In this sense, the environment we have in mind is broadly consistent with the model presented in the second chapter of my dissertation as well as Lorenzoni (2009) and Mendes (2007) As we just said, our assumptions are consistent with standard dispersed-information DSGE's and yet we do not to impose that structure ex ante. We see this as providing a more robust and data-driven framework that lets the data speak. In sum, our main assumption is a timing assumption. We maintain that the noise shock only impacts true values with a lag, through the decision making of agents who respond to the noise-ridden indicators they have at their disposal, pending the publication of more accurate figures. The paper is devoted to showing how this simple identification scheme delivers interesting business cycle effects of what we call revision or noise shocks. Indeed, output, unemployment and investment display statistically significant responses to a noise shock which can be thought of as a release of output growth number that does not reflect actual output growth.

Our work is related to those in Rodriguez-Mora and Schulstad (2007)[1] and Oh and Waldman, 1990 and 2005). In particular, Rodriguez-Mora and Schulstad (2007) go a long way to show the effect of data revisions on output growth and investment.

For the time being we take a clear stand in assuming that early vintages of data impact the true underlying values through the decision process of agents. We are aware of the criticism raised by Clements and Galvão (2010) who argue that the casual effects of early announcement of output growth numbers on future growth might not necessarily signal a behavioral relationship as Rodriguez-Mora and Schulstad (2007) posit but might be the by product of the specific statistical process for data revisions.

While we might consider this insight for future developments of our analysis[2], we see our current work as a simple and intuitive benchmark. Clements and Galvão (2010) need make assumptions on the revision process while we do not need to model it. Moreover, their analysis does not rule out the possibility of a behavioral relationship, rather it highlights the possibility that the data revision process itself might generate a specific correlation pattern between different releases.

Our exercise draws from general equilibrium models in which the casual relationship is straightforward. Relative to Rodriguez-Mora and Schulstad (2007), we see our methodology to be more general as it presents a simple VAR identification scheme which can be extended in numerous ways. Moreover, we focus our attention on impulse responses rather than predictive power. In this respect, we believe our work as some sort of a

[1]Kaukoranta (2009), expands Rodriguez-Mora and Schulstad (2007) on a longer series and more countries.

[2]Clements and Galvão (2010b) develop specific techniques for VARs with data revisions, which however they use primarily for prediction purposes.

bridge between the papers we just cited which tend to be geared towards a statistical analysis and recent works like Lorenzoni (2009) and Blanchard, L'Hullier and Lorenzoni (2011).

The former, identifies all non-technology disturbances as noise shocks, an extreme assumption which is entertained to show the ability of the model to match even the most extreme case. The latter tries to tell noise from news shocks without resorting to data revisions.

Indeed, our baseline VAR is, indeed, rather similar to that in Lorenzoni (2009)[3], comprises the final releases of output growth and unemployment together with the first release of output growth, which allows us to pinpoint the impact of noise shocks on real variables.

We believe that one of the main benefits of VAR analysis is its ability to isolate the part of the revision which is orthogonal to the variables of interest[4]. Moreover VARs can be easily seen as the econometric counterpart of dispersed information general equilibrium models.

The rest of the paper presents a discussion of the assumptions and the identification strategy, followed by the estimation of our baseline VAR as well as an alternative specification which includes a measure of investment on top of output growth and unemployment.

[3] We use unemployment instead of hours and consider output growth as opposed to levels. Obviously we also include the first release of output growth which does not enter Lorenzoni (2009)(?) VAR specification.

[4] Rodriguez-Mora and Schulstad (2007) have an ad-hoc equation to isolate what they call surprises.

2 Setup

2.1 Classical Noise

For the sake of the discussion let us assume that only two vintages of data are available. We will refer to the first release as y_t^0 and to the latest as y_0^fexplain the different cases for the latest

For the moment let us entertain the assumption which is commonly made in dispersed information economic models, i.e. the early vintage of data equals the first plus a noise shock:

$$y_t^0 = y_t^f + v_t$$

While a number of empirical papers discuss the true statistical properties of data revisions (e.g. Arouba (2008)) we start off with it because it is the one commonly used in modeling.

Consistent with our assumption, the first vintage of data we consider is the one published in the quarter following the one to which it refers. That way computation is made when the quarter has ended so that remaining imperfection should be more easily attributable to noisy data as opposed to a forecasting error.expad and note that this timing assumption also make the identification timing better because decisions are sunk... i guess. and consider whether to move it down in the more empirical section.

Our empirical analysis further maintains that behind the scenes is a model whose state equation can be summed up as follows[5]:

$$y_t^f = A(L)y_{t-1}^f + B(L)v_{t-1} + \varepsilon_t \tag{1}$$

[5] We do not tackle the issue of invertibility in this context, assuming it throughout, the aim of our work being primarily empirical.

Where all the elements of equation (1) can be vectors and $A(L)$ and $B(L)$ are finite-order polynomials in the lag operator.

Looking at equation (1) it should be clear that the what we refer to as final or latest release is the true economic variable, the one set by the agents in the model or by chance if exogenous. Implicitly we are assuming that the revision process eventually converges to the true underlying value.

what is there was still some unobserved error? This representation is consistent with a model in which agents' behavior is described by linear optimal responses given some information set.

In fact, our setup is consistent with models with dispersed information in which the history of signals enters the information set of the agents.

In particular, we have in mind a model in which agents act on a history of signals which include early releases of data, such as the one I study in the next chapter or Mendes (2007).

In those environments, agents receive all sorts of idiosyncratic signals which wash out in the aggregate and also economy-wide signals, which can be thought of as early data releases.

While the idiosyncratic information components do not directly show up in our state representation, they play a key role in preventing the revelation of the aggregate state.check if it is possible for the state not to be revealed even if only aggregate noise is there...

Equations (**??**) and (1) define the evolution of the two set of variables we are interested in, namely the early and the latest vintages of data.

Combining the two defines our model for the early releases of economic data:

$$y_t^0 = A(L)y_{t-1}^f + B(L)v_{t-1} + \varepsilon_t + v_t \tag{2}$$

which shows how the revision component affects directly the early vintage of data and indirectly, i.e. through the decision-making process of the economic agents, the future values of fundamental variables.

That is consistent with the idea that when early vintages of data are released, decisions for the period at hand are sunk[6] but future decisions will respond to this noisy indicator of economic activity.

2.2 Identification

The identification strategy hinges on the fact that the information set of the econometrician is richer than that of the economic agent who made the decision, because the econometric analysis is carried out at a later timeexpand on why we need to have some time after the end of the sample.

Rearranging equation (**??**) and substituting it into equation (2) yields:

$$y_t^0 = (A(L) - B(L))\, y_{t-1}^f + B(L)y_{t-1}^0 + \varepsilon_t + v_t \tag{3}$$

Using equation (3) to substitute for y_t^0 in equation (1) delivers a VAR representation of the final observations:

$$y_t^f = (A(L) - B(L))\, y_{t-1}^f + B(L)y_{t-1}^0 + \varepsilon_t \tag{4}$$

[6]This is certainly true in our case as we consider as first release the one published in the quarter following the one of interest.

Stacking up the early and the latest vintages produces the following VAR:

$$\begin{bmatrix} y_t^f \\ y_t^0 \end{bmatrix} = \begin{bmatrix} A(L)-B(L) & B(L) \\ A(L)-B(L) & B(L) \end{bmatrix} \begin{bmatrix} y_{t-1}^f \\ y_{t-1}^0 \end{bmatrix} + C \begin{bmatrix} \varepsilon_t \\ v_t \end{bmatrix} \tag{5}$$

As usual matrix C maps fundamental shocks into observed residual so it has to satisfy:

$$CC' = E\left[\underline{w}_t \underline{w}_t'\right] \tag{6}$$

Where $w_t = [\varepsilon_t \ v_t]'$. What we call noise shocks are identified by the fact that they contemporaneously affect only the early release of data. As described in the previous section, noisy components enter the decision making process of the imperfectly informed agents but they do so with a lag because when early numbers concerning period t are made public, decision for that period have been already made.

Suppose that the $n-th$ element of our VAR is the early release of output growth. Our identifying assumption implies that the $n-th$ column of C will have zero entries corresponding to final releases and a non-zero entry in row n.

The cases we will consider in the rest of the paper consider early output growth numbers as the only element of y_t^0 which lends itself neatly to a simple Cholesky identification scheme in which the early vintage of output growth enters at the bottom of the VAR.

2.3 Prediction Error

As mentioned above, a vast empirical literature shows that revisions for some series are better characterized as resulting from forecasting errors made by the agency which publishes early releases, e.g. Mankiw and Shapiro (1986).

The key difference with respect to the case illustrated above is that the revision is not orthogonal to the final release, which makes the revision not suitable candidate for a noise shock.

In this paragraph we illustrate how our VAR procedure actually mitigates this problem as what we call noise shock is *not* the revision of data vintages, but that part of the revision which is orthogonal to the final release.

An exhaustive discussion of this issue would require the knowledge of the prediction models used by the agencies which publish early vintages of data. Since that is not the case, we will proceed with an example and illustrate how it is robust to a simple statistical model. This example will illustrate to which extent our procedure is robust to different models used by the data-producing agency.

Let us assume that a statistical agency receives a noisy signal on the true underlying economic variable which takes on the following form:

$$y_t^{00} = y_t^f + v_t$$

The key difference with respect to the case above is that now the agency correctly anticipates that the data they collect are noise ridden and so perform a filtering procedure before making them public. In particular, it is reasonable to assume that they will consider the linear projection of the true underlying variable onto the known signal so that the early release would take on the following form:

$$y_t^0 = P[y_t^f | y_t^{00}] = \phi y_t^{00} = \phi y_t^f + \phi v_t$$

Where the projection coefficient ϕ depends on the relative variance of noise in the signal y_t^{00}.

The key difference, relative to the case above is that now the data revision is not orthogonal to the final release, in fact:

$$y_t^f - y_t^0 = (1-\phi)y_t^f + \phi v_t$$

As a consequence, one would be incorrect in taking the revision as an indicator of the noise shock. However, our VAR strategy provides a simple fix to this.

Under the maintained assumption that economic agents in the model know the data-generating process, the newly defined early release would simply result in a different observation equation but would otherwise not change the model which could be summed up as:

$$y_t^f = \tilde{A}(L)y_{t-1}^f + \tilde{B}(L)v_{t-1} + \varepsilon_t$$

Where different filters $\tilde{A}(L)$ and $\tilde{B}(L)$ reflect the different observation equation.

Following the same steps as above while using the new definition of early release on gets the following formulas for the early and the latest vintages of data:

$$y_t^0 = \phi(\tilde{A}(L) - \tilde{B}(L))y_{t-1}^f + \tilde{B}(L)y_{t-1}^0 + \phi\varepsilon_t + \phi v_t \quad (7)$$

$$y_t^f = (\tilde{A}(L) - \tilde{B}(L))y_{t-1}^f + \frac{1}{\phi}\tilde{B}(L)y_{t-1}^0 + \varepsilon_t \quad (8)$$

Despite the scaling factor ϕ showing up in the equations which, for instance, makes the response of the early release to a fundamental shock smaller than in the case above, it is still the case that the noisy component v_t only affects the early release contemporaneously while not the final, thus being consistent with the identification strategy laid down above. Not only that, but this analysis suggests that the resulting noise shock is the share of noise ϕ which is not filtered out by the statistical agency. In other words it is the chunk of noise that enters the economy through the informational set of agents[7].

[7] It does not seem that ϕ should drive the roots of the polynomial over one, because it shows up in the term in y_{t-1}^f in the equation for y_t^0 and vice versa, in the equation for y_t^f. In any case, in the limit

The example above illustrates a situation in which taking the data revision naively would lead to an incorrect assessment of the noise shock because the revision incorporates a component which is not orthogonal to the true value y_t^f. The VAR however cleanses the revision of the component that depends on y_t^f.

While the example assumes a very simple information set of the statistical agency it casts light on the benefits of our strategy, which whitens revisions so that we can call noise shock, the component of the revision which is orthogonal to the variables included in the VAR.

In fact, the only possible problem with this strategy appears to be in the number of variables and lags included in the VAR. In abstract, since the agents in the model know the data generating process, any variable or lag thereof used by the agency would be included in the state equation. In practice, since we do not know the information set and the procedures of the statistical agency we rely on the standard lag-selection tests to gauge whether our statistical model appears to be correctly specified.

So, while the limited number of data points limits the number of series and lags we can realistically include in our estimation we find that uses a VAR is the correct approach to isolate noise shocks as it orthogonalizes data revisions relative to the variables included in the estimation. This is somewhat related to Rodriguez-More and Schulstad (2007). say when you comment that includind investment does not change things a lot that it is good in this respect as it does not seem to be a major omitted vairable thing.

as $\phi \to 1$ which occurs when the agency has more precise information, the effect of ϕ becomes smaller and smaller.

3 VAR

3.1 Baseline

When it comes to deciding which variables should enter our VAR specification we start off with a parsimonious set, in part motivated by the fact that using different vintages of data increases the number of parameters to estimate on a relative small time series and in part because, as we said above, we would like to contribute to the evidence provided in Lorenzoni (2009). Different vintages of data are available only from the mid 1960's and we also want to leave a sufficiently long period after the end of the sample so that we can be reasonably confident that the bulk of the revisions has ended by the time we carry out are analysis. For this reason we limit our sample to 2006.

In a similar fashion to Lorenzoni (2009) we include the final releases of output growth and unemployment in y_t^f, adding the early release of output growth numbers in y_t^0. This is a simple enough setting and yet allows to study the impact of noise shocks on two crucial variables without assuming that all non-permanent effects are noise related as in Lorenzoni (2009).
Our estimation equation then reads:

$$\begin{bmatrix} \Delta y_t^f \\ u_t^f \\ \Delta y_t^0 \end{bmatrix} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} \begin{bmatrix} \Delta y_{t-1}^f \\ u_{t-1}^f \\ \Delta y_{t-1}^0 \end{bmatrix} + C \begin{bmatrix} \nu_t^1 \\ \nu_t^2 \\ \nu_t^3 \end{bmatrix}$$

What we are interested is the identification of the third column of matrix C which, consistent with the discussion in the previous section, will read:

$$C_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Which implies that the our empirical noise shock ν_t^3 will be orthogonal to all the variables included in the VAR except the current value of the first release (see the Appendix for details).

3.1.1 Data Description

We consider the real GDP and the unemployment rate from the Historical Data Files for the Real-Time Data Set provided by the Federal Reserve Bank of Philadelphia. The quarterly vintages and quarterly observations of the Real GNP/GDP (ROUTPUT) is in Billions of real dollars, and seasonally adjusted. We take the first difference logarithmic transformation, so we consider it as a quarterly (annualized) growth rate[8]. Instead, the quarterly vintages and monthly observations of the Unemployment Rate (RUC) is in percentage points, seasonally adjusted. We transform our data from monthly to quarterly frequency considering the first observation of the quarter.

We consider the quarterly sample from 1966:1 to 2006:4. This is so that we allow for a sufficiently long window for revisions even for the end-of-sample observations. In fact, our final releases are those published in the third quarter of 2011[9] so we allow for

[8]Using growth rates is motivated not simply by non-stationarity consideration but also by the fact that, as Rodriguez-Mora and Schulstad (2007) point out, it is easy to account for big long-term data revisions in growth rates (because typically affect one value which we substitute with the average of the previous and the following quarter) than in level, because in this case the effect of the revision is essentially permanent.

[9]Clements and Galvão (2010) entertain both the definition of final release as the latest available or that occurring a fixed number of quarters after the end of the period of interest (in their case 14

about five years worth of revisions even for the data at the end of the sample. For the first release, on the other hand, we considered that derived from output level numbers published one quarter after the period of interest[10]vertical difference of diagonal difference?. That way it seems safe to consider that the agency had some time to collect data, reducing the forecasting dimension and it also guarantees that such a number cannot affect the decisions of agents in the current period.

3.1.2 Results

Figures 1 and 2 report the responses of final output (in log-levels) and unemployment to a revision shock.

First, both of them are significant. Output appears to be higher than it would otherwise be for several quarters, while unemployment is significantly below its long-run level for around three years.

Interestingly, both responses build over time in a hump-shaped fashion which is consistent with learning in models with dispersed information.think about the scale

Moreover it should be noticed that not only the growth-rate of output converges back to zero but log-level do as well, which is consistent with the idea that while noise shocks can be expected to produce variability at business cycle frequency, no long-run effects on output seem likely.

Finally, the sign of the responses deserves some attention as well. Firstly, because the shock at hand is not technological in nature - it is a demand shock in the spirit of Lorenzoni (2009) - it is natural to expect that output and unemployment be negatively correlated. And so they turn out to be.

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quarters, seeming to favor the latter because it is less affected by long-term revisions. On the other hand, Rodriguez-Mora and Schulstad (2007) seem to favor our approach. In any event, we find our approach a sensible benchmark because the standard counterpart of our VAR would be one in which the latest releases available are used, not those published a certain fixed number of quarters after the end of the period of interest.

[10]The computer code we used to elaborate raw data can be requested to the authors.

Finally, the response to a positive noise shock is an increase in output. This might have to do with a coordination effect. Since all agents see higher-than-should-be output-growth all tend to produce a bit more than they would otherwise. As a consequence, unemployment will fall[11]. [inline]discuss the sheer size of the shock and responses if possible

3.2 Investment

Rodriguez-Mora and Schulstad (2007) suggest that investment is a crucial variable when considering the impact of data revisions, which is reasonable given the forward-looking nature of investment decisions.

Long-term projects, such as investment plans tend to be, are more susceptible to data imperfections as they necessarily have to rely on forecasts of future conditions. On top of that, investment decisions are costly to reverse, once undertaken.

Adding a measure of investment in our VAR we want to address two main points. First, we are interested in verifying if investment exhibits a significant response, somewhat along the lines of Rodriguez-Mora and Schulstad (2007). Secondly, introducing investment we can verify if the response of output to a noise shock is significant even when a measure of investment is included in the VAR.

Finally, adding an extra regressor further "cleanses" our definition of noise shock for potential correlations with variables which could enter, the data-publishing agency's information set. In particular, we make our noise shock orthogonal to lagged and current investment as well.

Our definition of investment is similar to that in Altig, Christiano, Eichenbaum, Linde

[11]In a general equilibrium model, things are more complicated as one should take into account the effect of the noise shock on pricing decisions and on the interest rate.

(2004), so, in fact, it is the log of the ratio of investment to GDP (in this case the final value of GDP). In other words, it is a measure of the investment-rate as a share of output.

In particular, the investment is given by the logarithmic transformation of the ratio between the sum of Gross Private Domestic Investment (GPDI) and Personal Consumption Expenditures in Durable Goods (PCDG) and the Gross Domestic Product, 1 Decimal (GDP). All the quarterly-observation variables used to build the series for investment were taken from the FRED Database of the Federal Reserve Bank of St. Louis.

3.2.1 Results

Results if Figure 3, 4 and 5 show that, once more responses to revision shocks appear to be significant at business cycle frequencies.

Interestingly, the size of the responses of output and unemployment is similar to that in the baseline setup we considered above, which appears to rule out the possibility that the response of output had to do with the omission of investment from the setup.

At the same time, the investment rate is higher than average for about two years following an "overly optimistic" early release of output growth numbers.

In this respect, it should be noticed that it is not simply investment per se that goes up, but investment as a share of output. Because output itself grows after a positive noise shock, this suggests that the level of investment increases in response to a noise shock more than output, consistent with basic business cycle facts that show how investment is positively correlated but more volatile than output (see King and Rebelo (2000)).

Finally, the sheer size of the responses appears to support the idea that noise shocks produce real effects even when cleansed from any linear correlation of the revision with lagged and current investment rates.

3.3 Variance Decomposition

While the significant responses of output, unemployment and investment to a noise shock suggest that revisions can play an important role in the behavior of macro variables, the share of the variance explained by noise shocks helps assess the relative magnitude of revision shocks.

Figures 6, 7 and 8 display a dynamic variance-decomposition exercise. Charts show the share of the variance explained by revision shocks at different points into the futurecheck that the description makes sense. In other words, they report the share of forecast variance which can be traced back to revision shocks.

The share is necessarily zero in the first period because of our identification restriction and then tends to grow leveling off just below 5 percent for what concerns output growth, around 7 percent for unemployment and 6 percent for investment.

These numbers help define the scope of noise shocks in a more precise manner compared to Lorenzoni (2009), who took a very conservative stance in assuming that all shocks that are not technological (and hence do not have a long-run effect in his setting) are to be regarded as potential noise shocks.

Here, on the other hand, we can more precisely assess the relative importance of revision shocks and we find the numbers sensible for two reasons. Firstly, they noise shock appear to represent a non-negligible share of the variability of key business cycle variables. Secondly, the share is small enough to be reconciled with common wisdom. Indeed, it seems that if noise shocks would explain say a third of the variation in output growth one could doubt the soundness of the analysis. It seems obvious that only a relatively small share of the variance of economic variables can be explained by noise shocks. At the same time, a shock explaining 7 percent of the variance of unemployment over the business cycle deserves attention.

Furthermore, Figures 6 and 7 also confirm that including investment share in the specification of the VAR does not dramatically impacts the ability of the VAR to explain the behavior of unemployment and output growth.

4 Conclusion

We set out to show how the use of different vintages of data delivers a simple identification strategy that allows to study the impact of data imperfections on the business cycle. Our findings suggest that an erroneous report of output growth numbers delivers a persistent and hump-shaped response of real output and unemployment. When we include investment in our estimation we find that it displays a significant response to noise shocks too, while the responses of output growth and unemployment are still significant.

Our analysis does not rely on a specific economic model although it is consistent with standard assumptions made in dispersed information models. At the same time, it acknowledges the fact that in the real world the revision of data need not be orthogonal to state variables as is usually the case in models (e.g. Mendes (2007)). That is why what we call noise shock is not the revision per se but a shock made orthogonal to the final-release variables included in the VAR.

As discussed in the introduction, we see our work as bridging a gap between more statistically-oriented papers and model-based analysis as that in Lorenzoni (2009)

In this respect, it is particularly useful to note that our estimation exercise delivers an estimate of the share of the variance of the economic variables that is explained by revisions, thus improving on the identification strategy employed in Lorenzoni (2009) which considered all non-permanent effects as noise-related. Our VAR suggests that between 4 and 5 percent of the variance of output growth can be attributed to noise shocks, with slightly higher share for unemployment and investment also due to revision shocks. We find this share as reasonable as revision shocks are certainly not the main driving force of the business cycle but at the same time turn out to be non-negligible. In fact, the quality of early data revisions turns out be a determinant of overall business cycle volatility.

In future developments we might consider refining the statistical methods used to treat different data vintages, possibly adopting those proposed by Clements and Galvão (2010, 2010b). In any event, we believe that using the latest revision is an important benchmark in that it is the series that one would normally use if he was not concerned with data revisions.

Moreover, one could also think of extending our variable se to possibly also accommodate the analysis of news shocks, see Barsky and Sims (2011, 2012).

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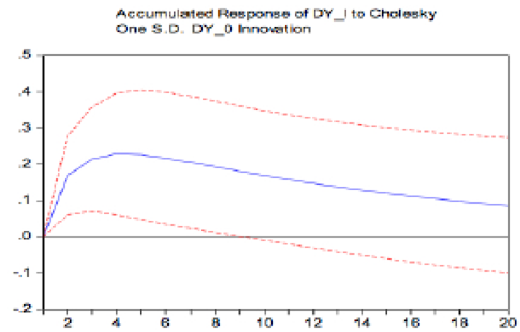

Figure 1.1. Impulse response (with confidence bands) of output to a one-stdev revision shock

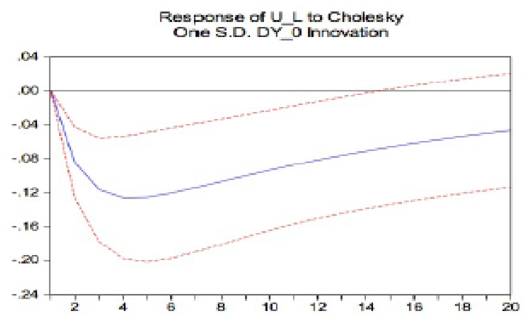

Figure 1.2. Impulse response (with confidence bands) of unemployment to a one-stdev revision shock

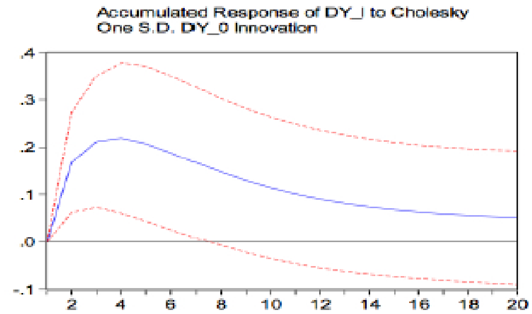

Figure 1.3. Impulse response (with confidence bands) of output to a one-stdev revision shock when investment is included in the VAR

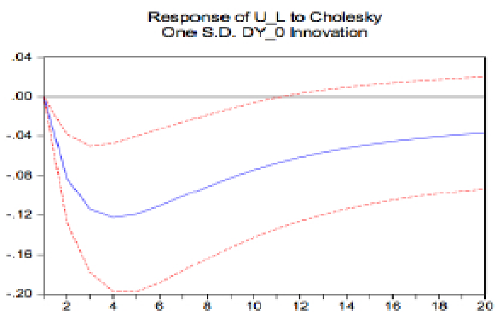

Figure 1.4. Impulse response (with confidence bands) of unemployment to a one-stdev revision shock when investment is included in the VAR

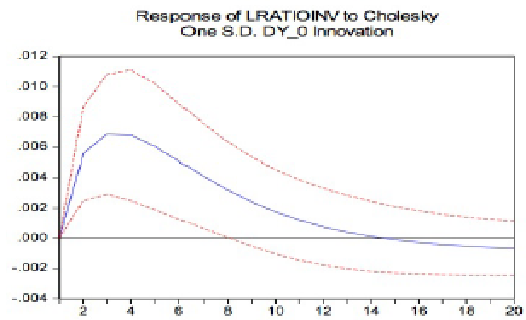

Figure 1.5. Impulse response (with confidence bands) of the investment ratio to a one-stdev revision shock

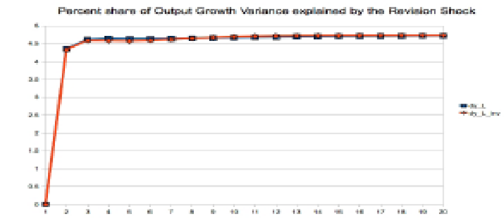

Figure 1.6. Variance share of Output Growth due to the revision shock in both the Baseline (squares) and the Alternative (triangles) setups.

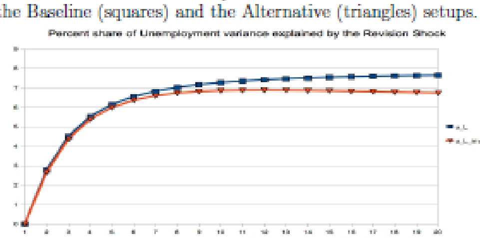

Figure 1.7. Variance share of Unemployment due to the revision shock in both the Baseline (squares) and the Alternative (triangles) setups.

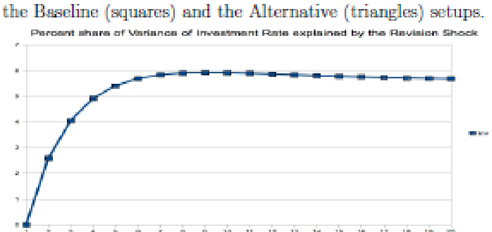

Figure 1.8. Variance share of the Investment Ratio due to the revision shock