

Enders, Zeno; Kleemann, Michael; Müller, Gernot

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Growth expectations, undue optimism, and short-run fluctuations

Zeno Enders, Michael Kleemann, and Gernot J. Müller*

– Preliminary and incomplete –
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Abstract

Expectations matter for economic activity. To the extent that they are fundamentally unwarranted, they represent “undue optimism or pessimism” (Pigou, 1927). In this paper, we identify the effects of optimism shocks on economic activity within a VAR model estimated on U.S. data. Identification rests on nowcast errors regarding current output growth, computed as the difference between actual output growth and the median forecast of professional forecasters. We assume that nowcast errors are either due to productivity or optimism shocks, but that the latter do not affect labor productivity in the long-run. We find that optimism shocks—in line with theory—induce a negative nowcast error, but stimulate economic activity. They account for up to 30% of short-run fluctuations of output.

Keywords: Undue optimism, Business cycles, nowcast errors,
VAR, Long-run restrictions

JEL-Codes: E32

*Enders: University of Heidelberg, zeno.enders@uni-heidelberg.de. Kleemann: Ifo Institute and LMU Munich, kleemann@ifo.de. Müller: University of Bonn, CEPR, and Ifo institute, gernot.mueller@uni-bonn.de. We thank participants of the 3rd CESifo conference on “Macroeconomics and Survey Data” as well as seminar participants at University of Heidelberg, Humboldt-University Berlin, and University of Dortmund for helpful discussions. The usual disclaimer applies.

1 Introduction

Economic behavior is driven by expectations about the current and future state of the economy. For instance, expecting a change of the productivity of a specific sector or the entire economy, households and firms will generally adjust their consumption and investment decisions. In fact, an influential contribution by Beaudry and Portier (2006) provides time-series evidence suggesting that business cycles are largely driven by expected future changes in productivity.¹ More generally, recent work by Jaimovic and Rebelo (2009) and Schmitt-Grohé and Uribe (2012) illustrates the potential of expected innovations in accounting for short-run fluctuations.

Given the importance of expectations for economic outcomes, it seems natural to ask to what extent economic fluctuations are driven by changes in expectations which are fundamentally unwarranted. Put differently, to what extent are changes of expectations an *autonomous* source of business cycle fluctuations? This question dates back to Pigou (1927) who discusses the possibility that “errors of undue optimism or undue pessimism” are a genuine source of “industrial fluctuations.”² More recently, Beaudry and Portier (2004) have explored this possibility of “Pigou cycles” in a quantitative business cycle model drawing on the distinction between shocks to actual and future productivity. Lorenzoni (2009), instead, shows how misperceptions regarding current productivity may give rise to demand shocks, while Angeletos and La’O (2012) illustrate the effects of sentiment shocks arising from undue optimism regarding ones’ terms of trade.

In this paper, we take up the issue empirically, that is, we explore the role of undue optimism and pessimism for business cycle fluctuations in U.S. time-series data. For this purpose, we aim to identify “optimism shocks”, i.e. changes in expectations due to a perceived change in fundamentals which eventually do not materialize. As recently stressed by Blanchard et al. (2011), this constitutes a formidable challenge, unless one resorts to estimating fully specified general equilibrium models (as in Barsky and Sims 2012). Specifically, as optimism shocks are changes in expectations unwarranted by fundamentals, they are essentially misperceptions or mistakes of economic agents. As such they cannot be uncovered on the basis of standard time-series techniques, unless the econometrician’s information set exceeds that of economic agents.

Our analysis is based on this insight. Specifically, we aim to identify optimism shocks which

¹Recent evidence by Leduc and Sill (2010) and Beaudry et al. (2011) supports this view, while Barsky and Sims (2011) find that the role of anticipated technological innovations for short-run fluctuations is rather limited.

²Keynes’ notion of “animal spirits” is a related but distinct concept. Keynes’ animal spirits are “a spontaneous urge to action rather than inaction”, which drive economic decisions beyond considerations based on “on nothing but a mathematical expectation” (Keynes 1936, p. 161 and 162).

pertain to the current, rather than the future state of the economy. Regarding the latter, we focus on productivity as a key indicator for agents' long-run economic prospects. Given this focus, we start our analysis with a reduced-form measure of agents' misperceptions, namely *nowcast errors* regarding current output growth, drawing on data from the Survey of professional forecasters. Maintained by Federal Reserve Bank of Philadelphia it asks participants to estimate a current quarter's output growth.

In a first step of our analysis we document the extent of nowcast errors, that is, the difference between the actual growth and the median prediction. Actual growth activity may deviate from expectations for a number of reasons. We find that nowcast errors are not significantly affected by monetary policy shocks or tax shocks, but by shocks to total factor productivity. We also document that nowcast errors are expansionary in that they are associated with a hump-shaped and persistent increase in future output.

In a second step, we seek to disentangle optimism shocks and unanticipated productivity shocks. For this purpose, we estimate a vector autoregression (VAR) model on time-series data for the U.S. In addition to nowcast errors, we include measures for labor productivity and employment in the VAR model. To identify optimism and productivity shocks we impose three restrictions. In the spirit of Gali (1999), we impose long-run restrictions according to which optimism shocks are not allowed to impact labor productivity in the long-run. Moreover, we assume that nowcast errors—both in the short and in the long-run—are only affected by the optimism shock and by unanticipated productivity shocks. This assumption appears warranted given that other shocks impact both the nowcast of economic activity and its actual realization. As a key result of our analysis, we find that optimism shocks, in line with theory, induce a negative nowcast error, yet boost economic activity.

So far, there are few attempts to identify optimism shocks empirically without imposing a fully structural model on the data. Blanchard (1993) provides an animal-spirits account of the 1990–91 recession focusing on consumption. Carroll et al. (1994) show that consumer sentiment forecasts consumption spending—aside from the information contained in other available indicators. Yet in concluding they suggest a “fundamental explanation” of this finding based on habits and precautionary saving motives. Oh and Waldman (1990, 2005) show that “false macroeconomic announcements”, identified as measurement error in early releases of leading indicators, cause future economic activity. They refrain from a structural interpretation however.³ Finally, Bachmann and Sims (2012) explore the importance of confidence for the transmission of fiscal shocks, rather than the effect of exogenous variations in confidence.

³In related work, Rodriguez Mora and Schulstad (2007) show that once announcements regarding current growth are taken into account, the actual of growth rates (the final release) has no predictive power in determining future growth at any future time.

The remainder of the paper is organized as follows. The next section characterizes the data, notably nowcast errors and documents their effect on economic activity. Section 3 presents a simple model which allows us to clarify issues pertaining to the notion of optimism shocks and its identification. Section 4 put forward our VAR model and presents results. A final section concludes.

2 A reduced-form measure of misperceptions

Eventually, we aim at uncovering the effects of *optimism* shocks, that is, misperceptions regarding current potential output. This measure, however, is not directly observable as surveys typically ask for estimates of actual output. We therefore start our analysis by computing an observable, but reduced-form measure of misperceptions, namely *nowcast errors* regarding current U.S. output growth. In the following, we describe the construction of nowcast errors and compute a number of statistics in order to illustrate their scope, possible causes, and their relation to economic activity. They represent a reduced-form measure since generally, they be a function of structural shocks. Nowcast errors will play a key role in our identification scheme, which is employed in section 4.

2.1 Data

Our main data source is the survey of professional forecasters (SPF), initiated by the American Statistical Association and the NBER in 1968Q4, now maintained at the Federal Reserve Bank of Philadelphia.⁴ The survey is conducted at quarterly frequency. Panelists receive the questionnaires at the end of the first month of the quarter and have to submit their answers by the 2nd to 3rd week of the following month. The results of the survey are released immediately afterwards. At this stage, no information regarding current output is available from the Bureau of Economic Analysis (BEA). Yet, in order to nowcast output growth for the current quarter, forecasters may draw on the NIPA advance report regarding output in the previous quarter.

Quarterly output growth is annualized and measured in real terms. Note that initially, within the SPF, output is measured by GNP, later by GDP. We compute nowcast errors by subtracting the survey's median forecast from the actual value reported by BEA.⁵ We compute two

⁴Professional forecasters are mostly private, financial-sector firms. The number of participants declined from 50 to fewer than 20 in 1988. After the Philadelphia Fed took over in 1990 participation rose again, see Croushore (1993). Regarding our latest observation in 2012Q4, 39 forecasters participated in the survey.

⁵Prior to 1981Q3 the SPF asks for nominal GNP. In this case, the forecast for the price index of GNP is applied to obtain the implied forecast for real GNP. For the SPF forecasts of GNP/GDP after 1981Q3 we use the series DRGDP2 which we obtain from the real-time data set of the Philadelphia FED. This series provides the median forecast of the quarterly growth rate of real output, seasonally adjusted at annual rate, with real

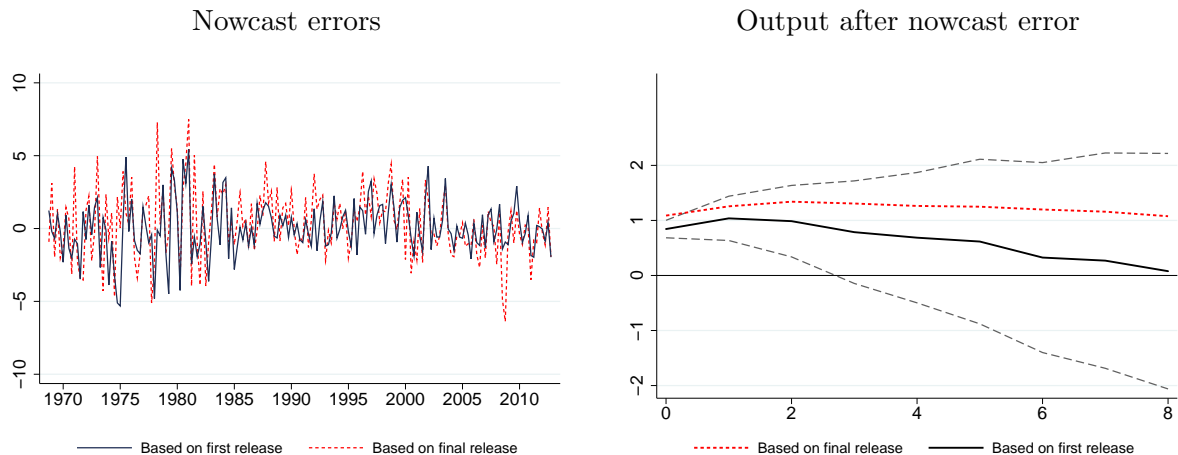


Figure 1: Nowcast error. Left panel: series based on final-release data (solid) and first-release data (dashed). Errors are measured in annualized percentage points (vertical axis). Right panel: cumulative impulse response of output growth to nowcast error based on local projections. Horizontal axis measures quarters, vertical axis measures percentage deviation of output from the average-growth path. Dashed lines indicate 90 percent confidence bounds implied by Newey-West standard errors.

measures of nowcast errors by distinguishing between the first and the final data release for actual output growth. For the latter, we use the latest available data vintage.⁶ Thereby we address fact that the assessment of nowcasts, or more generally, forecasts depends on what is being used as the “actual” or realization (see, e.g., Stark and Croushore 2002).⁷

2.2 Nowcast errors

We plot quarterly nowcast errors regarding current output growth in the left panel of figure 1, measured in annualized percentage points. The solid (dashed) line represents results based on final-release (first-release) data. Although the two series co-move strongly (correlation: 0.55), there are perceptible differences. For instance, there are sizable negative errors in the second half of 2008 only for the measure based on final-release data. Presumably, at the beginning of the great recession, the actual growth slowdown was larger not only relative to what professional forecasters predicted in real time, but also relative to what initial data

GNP prior to 1992 and real GDP for 1992-present.

⁶Data are obtained from the Philadelphia FED’s real time database and BEA, respectively. First-release data: BEA’s first (advance) estimate of the quarterly growth rate of real GNP/GDP (seasonally adjusted at annual rate, with real GNP prior to 1992 and real GDP for 1992-present): ROUTPUT. Final-release data: series GNPC96 and GDPC96 which are quarterly Gross National/Domestic Product, seasonally adjusted at annual rates, chained 2005 Dollars.

⁷In fact, the authors consider a set of alternative definitions of actuals and find statistically significant differences of forecast evaluations for real output. For our purposes, however, results are hardly affected by the choice of first- or final-release data, as shown below.

Table 1: Summary statistics nowcast errors

	N	Mean	SD	Min	Max	Ljung–Box test	
						Q	$p > Q$
Based on final release	177	.35**	2.36	-6.38	7.49	2.59	.96
Based on first release	177	.04	1.86	-5.31	5.43	8.68	.37

Notes: Nowcast errors computed on the basis of final-release (top row) and first-release (bottom row) data; sample: 1968q4 - 2012q4. Means are tested against zero based on a standard t-test. ‘***’ indicates significance at the 5% level. The last two columns report Q-statistics and p-values for the Ljung–Box test for autocorrelations up to 8 lags.

suggested. Moreover, errors based on first-release data are shifted downwards relative to those based on final-release data, notably in the first half of the sample.

This is confirmed by the summary statistics reported in table 1: the mean of the nowcast errors is significantly positive if we consider final-release data, but not significantly different from zero in case of first-release data.⁸ The standard error and the largest realizations of the nowcast error are also considerably larger in case of final-release data.⁹ Finally, the last two columns of table 1 report results of a Ljung–Box test suggesting that there is no serial correlation in both series.

What causes nowcast errors? Assuming that the average forecaster has a correct understanding of the economy, structural innovations which are public information should not induce systematic forecast errors. On the other hand, structural innovations which are not directly observable may generate nowcast errors. To assess this hypothesis, we run regressions of nowcast errors on popular (and relatively uncontroversial) series of structural innovations. Specifically, we consider monetary policy shocks identified by Romer and Romer (2004), tax shocks identified by Romer and Romer (2010), and productivity shocks provided by Fernald (2012), who uses the method of Basu et al. (2006) on a longer sample.¹⁰

In each instance, we regress nowcast errors on the contemporaneous realization of the struc-

⁸See Zarnowitz (1985) for an early assessment the rationality of SPF forecasts. Considering revised data the author confirms our finding of bias towards positive nowcast errors for real GNP/GDP that is attributed to an persistent underestimation of inflation during the 1970s. However, Zarnowitz finds no evidence for irrationality in the sense of inefficient use of relevant information based on autocorrelation tests.

⁹This finding is consistent with earlier evidence by Zellner (1958) and Cole (1970) showing that the revisions of GNP are serially correlated.

¹⁰In terms of actual series we use the “utilization-adjusted TFP in producing non-equipment output” (dtfp_C.util) of Fernald (2012). In case of monetary and tax shocks we use the quarterly average of the monthly shock series (–RESID–) and the “sum of Deficit-Driven and Long-Run Tax Changes” (EXOGENR-RATIO), respectively.

Table 2: Nowcast errors and structural innovations to...

	Monetary Policy 1969:1 - 1996:4	Taxes 1968:4 - 2007:4	Productivity 1968:4 - 2009:3
Based on final release	1.678 (1.044)	-.002 (1.144)	.480*** (.049)
Based on first release	1.611 (.978)	-.730 (.963)	.140*** (.045)

Notes: Impact effect on nowcast error obtained from regressing the nowcast error on the time series for the structural innovations to monetary policy, fiscal policy (taxes) and productivity. The regression includes four lags of the nowcast error. Newey-West standard errors being robust for autocorrelation up to four lags are reported in parentheses. Time series of structural innovations to monetary policy, taxes, and productivity are due to Romer and Romer (2004), Romer and Romer (2010), and Fernald (2012).

tural shock, while adding four lags of the nowcast error to the regression. The sample varies across regressions, as we use the longest overlapping sample in each case. Results for the impact effect are reported in Table 2. Newey-West standard errors are reported in parentheses. The top row reports results based on the final-release data, the bottom row reports results based on the first-release data. We find that for monetary and fiscal policy innovations there is indeed no significant impact on nowcast errors, implying that the effect of publicly available shocks is relatively well understood by the forecasters. Productivity innovations, instead, have a significant impact. Specifically, positive productivity innovation tend to raise the nowcast error contemporaneously.

2.3 Nowcast errors and economic activity

Nowcast errors are positive surprises regarding current activity. They are, unsurprisingly, positively correlated with economic activity.¹¹ To explore systematically how current nowcast errors relate to economic activity we estimate the dynamic relationship on the basis of local projections (see Jordà 2005). Specifically, we relate current and future output growth to current nowcast errors.¹²

The right panel of Figure 1 shows the cumulative impulse response of output growth to a

¹¹The correlation between GDP (final-release data) and the nowcast error is .73 and .47 for the final-release and first-release measure, respectively.

¹²To capture potential serial correlation, we apply Newey-West standard errors. The error structure is assumed to be heteroskedastic and possibly autocorrelated up to lag 4.

nowcast error. The horizontal axis measures quarters, the vertical axis measures percentage deviation of output from the constant-growth path. Dashed lines indicate 90 percent confidence bounds implied by Newey-West standard errors. We find that nowcast errors predict a strong, and mildly hump-shaped increase of economic activity. The effect is stronger for our measure based on the final-release data, but differences relative to the one based on first-release data are moderate. The finding that the (reduced-form) nowcast errors predict future activity is noteworthy in light of the evidence on the effects of optimism shocks provided in section 4 below. To obtain this evidence, we rely on identification restrictions which we motivate in the following section.

3 Model

In this section we develop a model which allows us to formally define optimism shocks, discuss conditions under which they may affect economic activity and, importantly, clarify issues pertaining to identification. The model is kept deliberately simple so as to highlight the role of informational frictions.

3.1 Setup and timing

A unit mass of households, indexed by $i \in (0; 1)$, and a unit mass of producers, indexed by $j \in (0; 1)$, populate a closed economy. Each household buys a different consumption bundle, consisting of a subset of all domestically produced goods. Each producer sells one of these differentiated products, manufactured with heterogeneous productivity levels, where productivity consists of a permanent aggregate and a temporary idiosyncratic component. Financial markets are complete.

The timing of events is as follows. Information about all variables of period $t - 1$ is released at the beginning of period t , that is, all agents receive the same, complete information about the past. Furthermore, a public signal about average productivity of period t is observed by all agents in the economy. Producers additionally know their own productivity as private information. At this stage, prices have to be set for the rest of the period. Based on public information, the central bank simultaneously sets the interest rate for financial investments between periods t and $t + 1$. This implies that monetary policy shocks are known at the time of price-setting. Still at the same stage, domestic financial markets open and households receive their payments from state-dependent assets. Their wealth thus equalizes. Households can decide between consuming and buying new state-dependent assets throughout the whole period, as financial markets remain open.

Crucial in this setup is the nature of the public signal about current aggregate productivity.

It is correct on average but may feature ‘optimism shocks’, thereby over- or underpredicting realized productivity. If producers make a mistake at nowcasting productivity after having combined the public signal with their private information, we speak of a nowcast error.¹³

After prices and the interest rate have been set, consumers buy their bundles, each consisting of a subset of all goods in the economy. Given that they observe the prices of the goods they buy, from which they can induce productivity levels of the producers included in their subset, they make a more accurate nowcast and adjust their shopping behavior accordingly. Because common technology follows a unit root process and it is expected that all households will have equal wealth and equal information in the next period, agents assume to be in a new steady state from period $t + 1$ onwards.

3.2 Households

Household i maximizes lifetime utility

$$U_t(i) = E_t^i \sum_{k=t}^{\infty} \beta^{k-t} \ln C_t(i) - \frac{L_t^{1+\varphi}(i)}{1+\varphi} \quad \varphi \geq 0,$$

with E_t^i being the expectational operator based on household i 's information set. $C_t(i)$ is the amount of consumption bundles consumed by household i , while $L(i)$ denotes its labor supply. We assume that each household works in equal proportions for each firm, such that wages are the same across households and firms. When maximizing this function, the household has to observe the following budget constraint featuring complete markets

$$Q_t B_{t+1}(i) + P_t(i) C_t(i) \leq D_t + L_t(i) W_t + B_t(i),$$

where $P_t(i)$ is the price index of household i 's consumption bundle. D denotes potential profits of the producers, shared equally among all households, and $B_t(i)$ are payments from the set of state-dependent assets bought last period at the price $Q_{t-1}(i)$. The bundle $C_t(i)$ of goods purchased by consumer i consists of a subset $n(i)$ of all goods

$$C_t(i) = \left(\int^{n(i)} [C_t^j(i)]^{\frac{\varepsilon-1}{\varepsilon}} dj \right)^{\frac{\varepsilon}{\varepsilon-1}},$$

where $C_t^j(i)$ denotes the amount of good j bought by household i . While each household purchases different goods, we assume that the amount n of goods bought is the same for all households. The price index of household i is

$$P_t(i) = \left(\int^{n(i)} P_t(j)^{1-\varepsilon} dj \right)^{\frac{1}{1-\varepsilon}},$$

¹³The term nowcast error refers to the fact that agents guess aggregate productivity in the same period, which has already realized.

with $P_t(j)$ denoting the price of good j .

3.3 Producers and monetary policy

Producer j produces according to the following production function, featuring a bundle of labor from all households as the sole input

$$Y_t(j) = A_t(j)L_t(j).$$

The central bank follows a standard Taylor rule but sets the interest rate before observing prices

$$r_t = \psi E_t^{cb} \pi_t.$$

Its information set, reflected in the operational operator E_t^{cb} consists of public information only, i.e. the central bank has no knowledge about the producers' idiosyncratic productivity levels.

3.4 Technology and signal

Log-technology of each firm is the sum of an aggregate and an idiosyncratic component

$$a_t(j) = x_t + \eta_t(j),$$

where $\eta_t(i)$ is white noise and aggregates to 0. The aggregate component x_t follows a random walk

$$x_t = x_{t-1} + \nu_t. \tag{1}$$

In the beginning of each period, each producer receives information about her productivity $a_t(i)$ and a public signal about x_t . This signal takes the form

$$s_t = x_t + e_t,$$

where e_t is an 'optimism' or 'pessimism shock' that can result in a nowcast error. This setup creates a signal-extraction problem, governed by the relative size of the variances of x , ν , and e , denoted by σ_η^2 , σ_ν^2 , and σ_e^2 . The model therefore nests the case of complete information about all relevant variables if $\sigma_e^2 = 0$. If $\sigma_e^2 > 0$, producers will sometimes set prices based on overly optimistic or pessimistic nowcasts.

3.5 Model solution

Market clearing requires that all produced goods are consumed

$$\sum_{i,j} C_t^j(i) = \sum_j Y_t(j)$$

and that all employed labor is supplied by households

$$\sum_i L_t(i) = \sum_j L_t(j).$$

We linearize the first-order conditions around the symmetric steady-state, allowing us to derive closed-form solutions of the approximate model. Agents in the model expect a jump to the new steady state in the period after the shock (the state variable technology follows a unit root, while complete markets eliminate heterogeneity other than in the period of the shock). Hence, using this long-run solution for period $t + 1$ to find expectations of price-setters and consumers while observing their respective information sets, we can also solve for the short-run variables in period t . Prices (in percentage deviations from the initial steady steady) are set according to

$$p_t(j) = \frac{1 + \varphi}{1 + \varphi\varepsilon} \left[E_t^j a_t - a_t(j) \right] + E_t^j p_t,$$

where E_t^j denotes expectations of producer j at the beginning of period t and p_t is the overall price level in the economy. Given the technology process (1), expectations about the average productivity $E_t^j a_t$ equal $E_t^j x_t$. To form a nowcast about aggregate productivity, producer j uses a Kalman filter (note that by assumption $x_{t-1} = 0$, as we analyze the effects of isolated shocks)

$$E_t^j x_t = \rho^p [\delta^p s_t + (1 - \delta^p) a_t(j)],$$

where ρ^p and δ^p depend on σ_e^2 , σ_ν^2 , and σ_η^2 . These variances are the same for all producers, such that the weights used in the Kalman filter are also identical across producers. After prices are set, each household observes a fraction n of all prices in the economy. Since the productivity signal is public, $a_t(j)$ can be calculated from $p_t(j)$ for each good. Hence, household i forms its expectations about the aggregate productivity according to

$$E_t^i x_t = \rho^h [\delta^h s_t + (1 - \delta^h) \tilde{a}_t(i)],$$

where $\tilde{a}_t(i)$ is the average over all $a_t(j)$ in household i 's sample. ρ^h and δ^h depend on σ_e^2 , n , σ_ν^2 , and σ_η^2 and are equal across households. Consumption then follows a standard Euler equation with household-specific inflation $\pi(i)$, as only a subset of goods is bought

$$c_t(i) = E_t^i c_{t+1} - r_t + E_t^i \pi_{t+1}(i).$$

Future consumption c_{t+1} is not indexed to the household, as equal consumption levels are expected across households because of complete markets. This new steady state in $t + 1$ allows us to obtain analytical solutions for today's variables. Aggregating and solving yields

$$y_t = Bx_t + (1 - B)E_t^h x_t$$

with $0 < B \equiv \frac{1+\varphi}{1+\varphi\varepsilon} [1 - \rho^p(1 - \delta^p)] < 1$ and E_t^h denoting the average expectations of households. Note the difference in information sets: households' expectations $E_t^h x_t$ are formed after observing a subset of prices, information unavailable for producer's (average) expectations E_t^p at the time of price setting. As visible in the above equation, output increases after positive fundamental shocks ($x_t > 0$), but also after optimism shocks ($e_t > 0$) that lead to too high expectations $E_t^h x_t$ of current fundamentals.¹⁴ Together with the aggregated updating formulae

$$\begin{aligned} E_t^h x_t &= \rho^h [\delta^h s_t + (1 - \delta^h)x_t] \\ E_t^p x_t &= \rho^p [\delta^p s_t + (1 - \delta^p)x_t] \end{aligned}$$

we can solve for s_t and x_t , if we observe y_t and E_t^p . This corresponds to our econometric exercise, in which we employ data on expectations and output and aim to disentangle nowcast errors that result from changes in fundamentals from those that are due to optimism shocks. The sign of the nowcast error

$$y_t - E_t^p y_t = E_t^h x_t - E_t^p x_t - B(E_t^h x_t - x_t) \quad (2)$$

depends on which of the two shocks has occurred. After an *optimism shock* ($x_t = 0, e_t > 0$), we have $E_t^h x_t - E_t^p x_t < 0$ because the better-informed households are closer to the true value of x_t than producers. However, as at least some weight is still placed on the signal, we also have $E_t^h x_t - x_t > 0$. We thus obtain

$$y_t - E_t^p y_t < 0,$$

a negative nowcast error made by the producers. Note that the same is true if instead of producers' expectations those of households are employed to calculate the nowcast error. After a *fundamental shock* ($x_t > 0, e_t = 0$), on the other hand, we get $E_t^h x_t - E_t^p x_t > 0$ and $E_t^h x_t - x_t < 0$ because of the opposite argumentation as above. Hence, in this case

$$y_t - E_t^p y_t > 0,$$

representing a positive nowcast error. The model therefore predicts that after an *optimism shock* for aggregate variables

- $y_t \uparrow$ in the short run
- $y_t - E_t^p y_t \downarrow$ in the short run

¹⁴Note that while this effect works via prices, real factors such as investment decisions based on expectations would have a similar impact and hence reinforce it.

- $y_t - n_t = a_t = 0$ in the short- and long run.

Furthermore, after a *fundamental shock*

- $y_t \uparrow$ in the short and long run
- $y_t - E_t y_t \uparrow$ in the short run
- $y_t - n_t \uparrow$ in the short and long run.

Any other shock that is observed by all agents (i.e. which enters information sets of consumers and producers) leaves $y_t - E_t y_t$ at zero. This last observation, which is in line with our results in table 2, together with the long-run predictions for labor productivity $y_t - n_t$ are key for our empirical identification scheme. Put differently, the insight that optimism shocks are the only ones that drive a wedge between expected and realized fundamentals while not having a long-run effect on labor productivity in the long run will be used as our identifying assumption. Note that interpreting the simple difference between expected and realized values of GDP as optimism shocks would lead to biased results.

4 The effects of optimism shocks

In this section, we aim at identifying optimism shocks in US time-series data on the basis of a VAR model. Our strategy combines long-run restrictions (as, for instance, in Gali 1999) with the insights into the nature of nowcast errors analyzed in Section 2 above. We discuss our VAR specification and identification strategy, before turning to the results.

4.1 VAR specification and identification

Our VAR model includes three variables. Under the baseline specification we include the nowcast error, e_t , the growth rate of labor productivity, Δx_t , and hours worked h_t .¹⁵ For our baseline specification, we compute the nowcast error using first-release data. Letting $y_t := \begin{bmatrix} e_t & \Delta x_t & h_t \end{bmatrix}'$ denote the vector of endogenous variables, the VAR model in reduced form reads as follows

$$y_t = \sum_{i=1}^L A_i y_{t-i} + \nu_t,$$

¹⁵Labor productivity is measured in terms of output per hour of all persons in the nonfarm business sector and hours worked is the natural logarithm of the corresponding hours, both series are obtained from the Bureau of Economic Analysis. Results are robust, however, once we measure labor productivity as output per person and hours as employment, both obtained from the Bureau of Labor Statistics. Furthermore, an alternative measure of productivity reacts similarly to our shocks as labor productivity, see section 4.3.

where L is the number of lags. ν_t is a vector of potentially mutually correlated innovations of which $\Omega = E \nu \nu'$ is the covariance matrix. We also include a constant in the VAR model.¹⁶ We estimate the model under our baseline specification on quarterly data covering the period 1980Q1–2012Q4. While our measure of nowcast errors is available since the late 1960s (see Section 2), we disregard observations prior to 1980 as the conduct of monetary policy arguably created the possibility of self-fulfilling expectations and changed considerably afterwards (Clarida et al. 2000).¹⁷ Below, also report results of a sensitivity analysis exploring the robustness of our results for the full sample.

Regarding the lag length, we attempt to account for concerns about the importance of the lag-truncation bias, notably if one imposes long-run restrictions on VAR models (see Chari et al. 2008). De Graeve and Westermarck (2013) provide Monte Carlo evidence suggesting that raising the number of lags can help to reduce the problem. For our baseline specification we thus use a rather long lag length of $L = 8$. We document below that results are robust with respect to a smaller number of lags.

We aim to identify structurally innovations, ε_t , with $\nu_t = B\varepsilon_t$ and $E\varepsilon\varepsilon' = I$. Given estimates for Ω and the A_i matrices, we identify B by simultaneously imposing short and long-term restrictions. Without loss of generality, we assume that ε_t contains from top to bottom a fundamental surprise shock (to labor productivity), the optimism shock, and a third shock to which we do not attach any structural interpretation. Key to our identification strategy is the insight that nowcast errors can only be the result of the first two shocks—both, in the short and in the long-run. Finally, as a third identification assumption, in line with our model outlined in the previous section, we assume that of those two shocks only fundamental surprise shocks can have permanent effects on labor productivity.

Formally, our identification assumptions impose the following restrictions on matrices B and A_0 , which determine the contemporaneous and the long-run impact, respectively:

$$B = \begin{bmatrix} * & * & 0 \\ * & * & * \\ * & * & * \end{bmatrix}, \quad A_0 \equiv \left(I - \sum_{i=1}^L A_i \right)^{-1} = \begin{bmatrix} * & * & 0 \\ * & 0 & * \\ * & * & * \end{bmatrix}.$$

4.2 Results

Figure 2 shows the results. The columns (from left to right) display the impulse responses to a fundamental surprise, an optimism shock, and the third shock. Solid lines represent

¹⁶We do not include a trend in our baseline, but consider alternative trend specifications in our sensitivity analysis due to the potential non-stationarity of the time series for hours worked.

¹⁷Alternatively, one might consider a later starting date for the sample in order to account for the decline in business cycle volatility after 1983 (McConnell and Perez-Quiros 2000). We find that results are not sensitive in this respect.

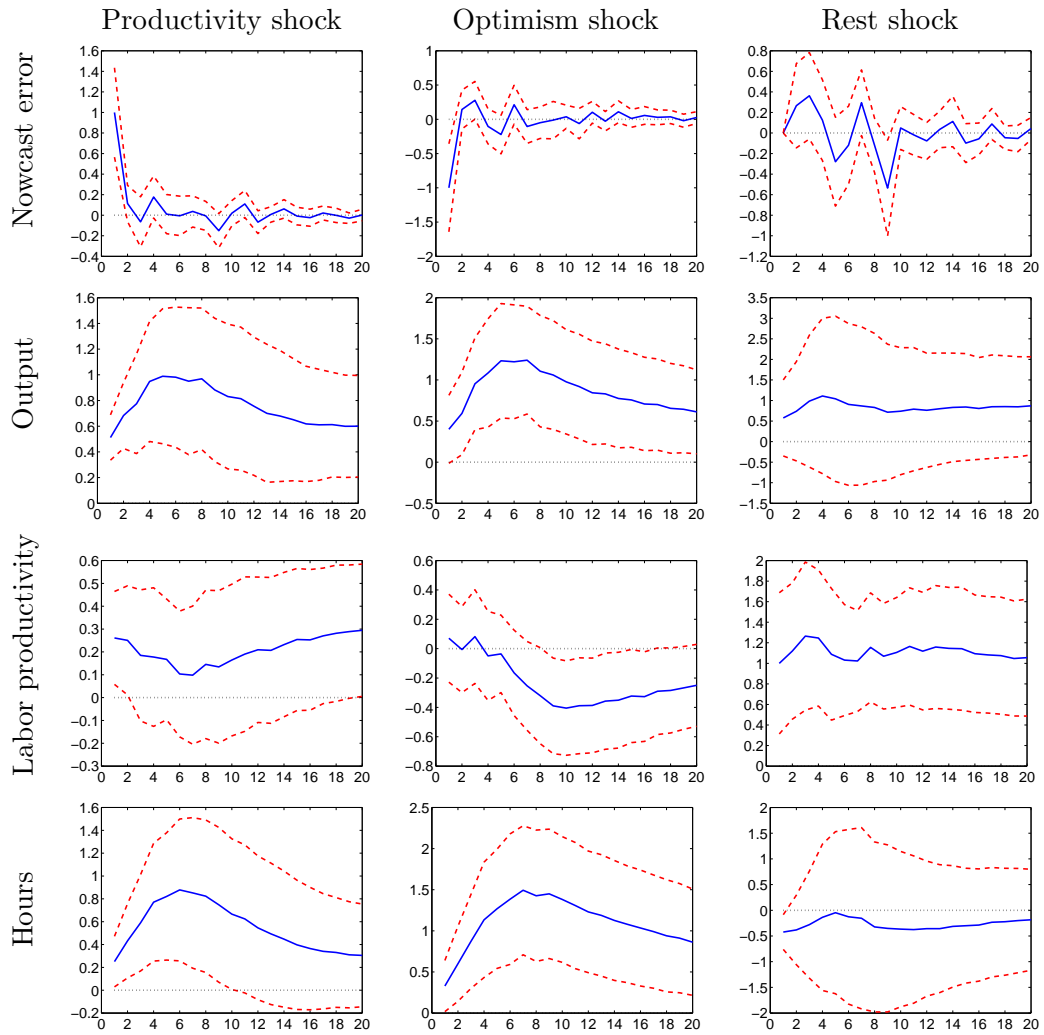


Figure 2: Impulse response functions to productivity and optimism shocks. Notes: results for baseline VAR model. Solid lines indicate point estimates, dashed lines 90% confidence bounds obtained by bootstrap sampling (1000 repetitions). Horizontal axes measure quarters. Vertical axes: percentage points in case of the nowcast error, percent otherwise.

the point estimate, while dashed lines indicate 90 percent confidence bounds obtained by bootstrap sampling. The rows display the responses of the nowcast error, output (implied by those of labor productivity and hours), labor productivity, and hours, respectively. In each case, horizontal axes measure time in quarters, while vertical axes measure percentage points in case of the nowcast errors and percentage deviations from trend otherwise. Recall that we only interpret the first two shocks structurally. They have been normalized to induce a nowcast error equal to 1 percentage point in absolute value (annualized) on impact while raising output.

A noteworthy result of our analysis is the response of the nowcast errors to productivity and optimism shocks. While both shocks are normalized to be expansionary, we find that productivity induce a positive response of the nowcast errors, while optimism shocks induce a negative response. Importantly, the sign of the response of the nowcast error to both innovations has been left unrestricted. Yet our findings regarding the response of nowcast errors are fully in line with the predictions of the model developed in Section 3 above, providing thus evidence in support of our identification strategy.

The second row displays the responses of output, implied by the joint response of labor productivity and hours. It increases strongly and in a hump-shaped way in response to productivity and optimism shocks. In fact, the short-run dynamics of output are fairly similar in response to both shocks. The impact increase is approximates 0.5 percent in both cases and the peak response is reached after about 6 quarters. While the peak response is somewhat stronger in case of an optimism shock, the response is more persistent in case of a productivity shock.

The third row shows the response of labor productivity. It increases in response to a productivity shock on impact, but also in the long run. Productivity declines in response to an optimism shock, but the response is only marginally significant. Note that optimism shocks are not allowed to impact labor productivity in the long run under our identification scheme. The responses of hours is shown in the last row. In the short run the response mimics that of output. It is somewhat weaker in case of productivity shocks and somewhat stronger in case of optimism shocks, reflecting the differential effect of these shocks on labor productivity. In the long-run hours are back to the pre-shock level.

In order to contrast the transmission of optimism shocks to those of productivity shocks it is of interest to investigate their effects on other variables than those included in the baseline model. To economize on the degrees of freedom we rotate additional variables into our baseline VAR model instead of hours. Figure 3 displays results for four additional variables of particular interest. We find that both, productivity and optimism shocks raise consumption

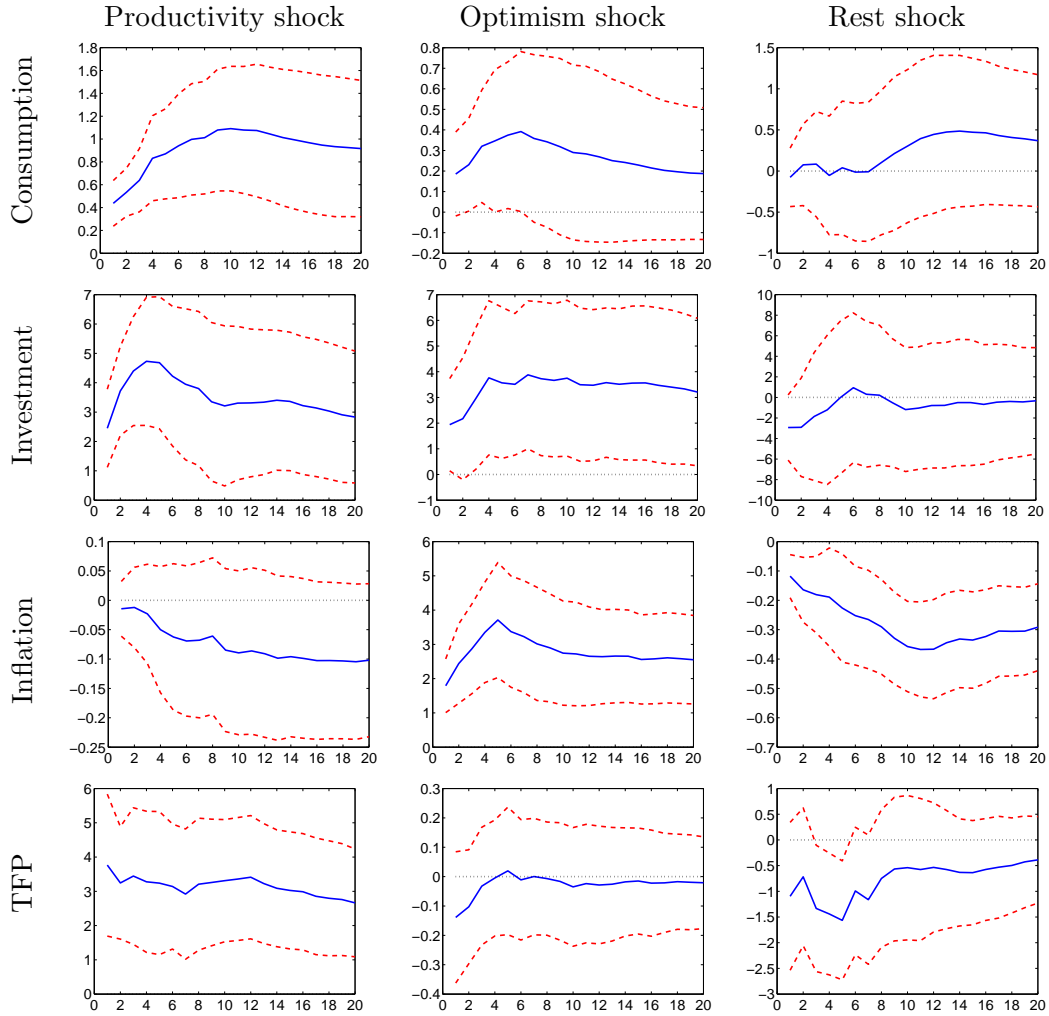


Figure 3: Impulse response functions to productivity and optimism shocks. Notes: each row displays the response of an additional variable (replacing) hours in the baseline VAR model, see Figure 2. Consumption is measured by real personal consumption expenditures, investment by real gross private domestic investment, both from the Bureau of Economic Analysis, inflation is the consumer price index for all urban consumers for all items less food and energy from the Bureau of Labor Statistics, and TFP is the utilization-adjusted TFP in producing non-equipment output series of Fernald (2012).

and investment, although the effect is somewhat stronger and more persistent in case of productivity shocks.

The third row of Figure 3 shows the response of core CPI inflation. We find that productivity shocks tend to be deflationary, although the response is not significant. Inflation responds immediately strongly to the optimism shock. The behavior of inflation is in line with the predictions of the model put forward in Section 3, thus lending support to our identification strategy. It also shows that these shocks have similar effects as traditional demand shocks.

Finally, as there has been a discussion in the literature if long-run movements in labor productivity indeed capture changes in technology, we analyze how productivity and optimism shocks impact on total factor productivity as measured by Fernald (2012). This series is constructed on the basis of utilization-adjusted factor inputs, as proposed by Basu et al. (2006). As it ends in 2009Q3, we estimate the VAR model on the longest available data series (1968Q4–2009Q3). The impulse responses of total factor productivity are shown in the last row of of Figure 3. We find that it increases strongly in response to productivity shocks identified on the basis of long-run restrictions, but not in response to the optimism shock. This result is consistent with the assumptions underlying our identification strategy.

In order to gauge the contribution of optimism shocks to economic fluctuations we compute a forecast error variance decomposition. Table 3 reports the results. We find that productivity and optimism shocks are responsible of two thirds and one third of variation in the nowcast error, respectively. This holds irrespective of the forecast horizon. Recall that in the short and long-run nowcast errors are restricted to be driven only by these two shocks. Regarding output, fundamental surprise shocks account for the bulk of fluctuations, also optimism shocks contribute substantially as well. In the short-run their contribution rises from 17 percent to almost one third after about three years and declines thereafter.

4.3 Sensitivity analysis

We conduct a number of experiments to explore the robustness of our results. First, we consider alternative measures of the nowcast error, which is key to our identification strategy. We have estimated the baseline VAR model using nowcast errors computed on the basis of first-release data. Results in Section 2 suggest that nowcast errors based on final-release data may differ substantially. We therefore estimate our VAR model while replacing the nowcast error based on first-release data with one based on final-release data. Results are shown in the left panel of Figure 4, confirming our findings for the baseline VAR model reported in Figure 2.

In what follows we explore to what extent results are robust once we consider a different

Table 3: Forecast error variance decomposition

		Productivity	Optimism	Rest
Nowcast Error	1	69.83	30.16	0.00
	4	66.57	30.38	3.05
	12	61.27	29.94	8.79
	40	60.78	30.02	9.20
Output	1	64.77	17.07	18.16
	4	55.29	27.82	16.89
	12	55.09	32.77	12.14
	40	53.67	25.79	20.54
Labour Productivity	1	23.41	0.75	75.84
	4	14.06	0.44	85.50
	12	9.63	8.77	81.61
	40	20.78	6.50	72.72
Hours	1	42.10	31.29	26.61
	4	50.29	45.76	3.94
	12	42.31	55.90	1.79
	40	35.26	62.88	1.85

Notes: FEVD for baseline specification.

SPF final release data

Bloomberg survey on industrial production

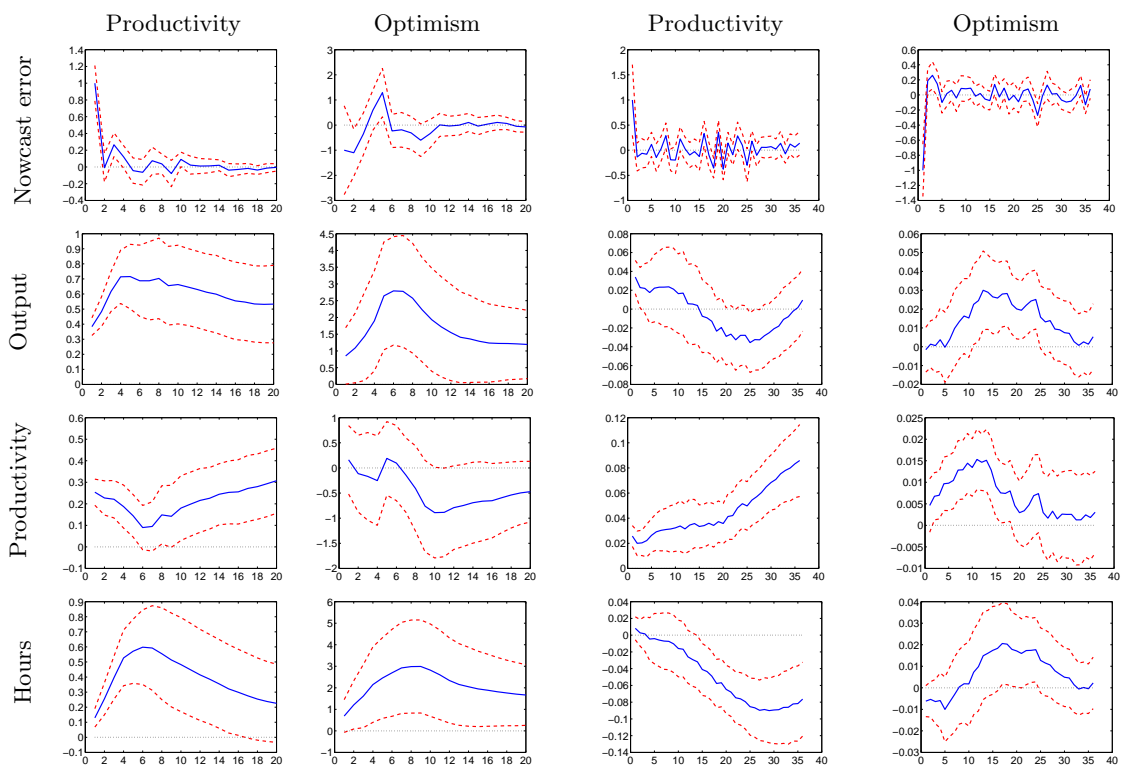


Figure 4: Impulse response functions to productivity and optimism shock: Sensitivity analysis I. Notes: left panel shows results for nowcast error based on final-release data, see Figure 2; right panel shows results for nowcast error based on monthly data for industrial production, horizontal axis measures months.

Sample starts 1968

Four lags

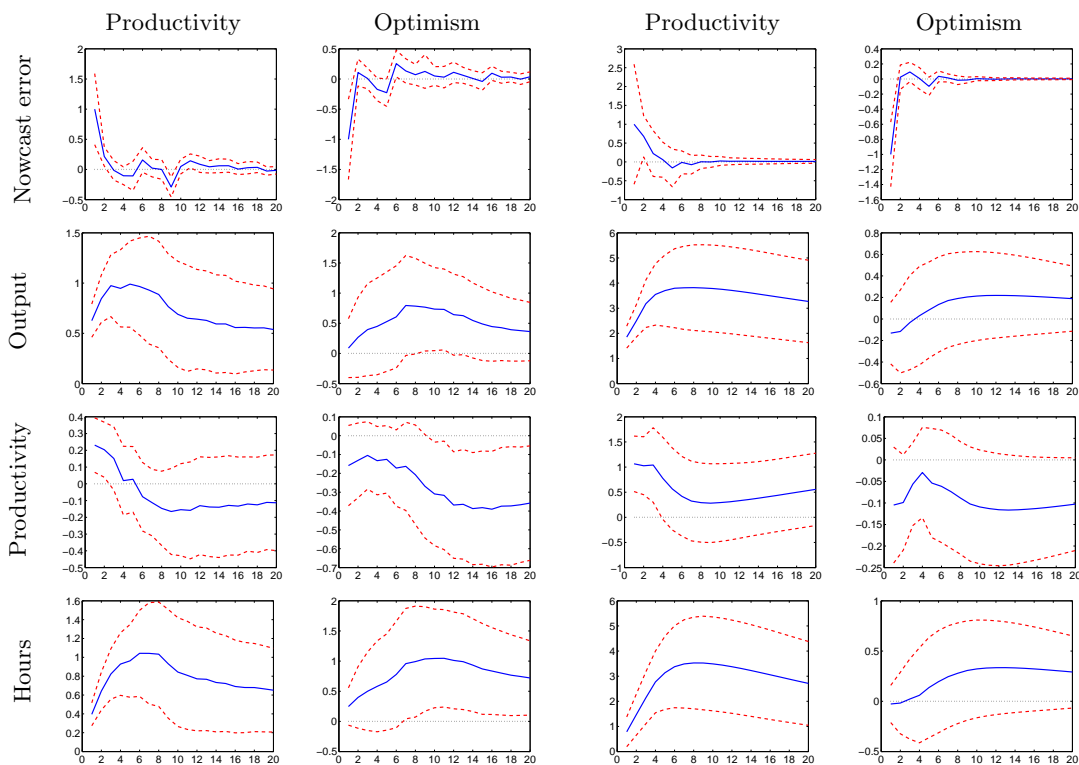


Figure 5: Impulse response functions to productivity and optimism shock: Sensitivity analysis II. Notes: left panel shows results for baseline VAR model estimated on sample starting in 1968Q4, see Figure 2; right panel shows results for VAR model with four lags.

sampling frequency, as our identification strategy relies on assumptions regarding the available information at the time forecasters are asked to predict current output growth. Specifically, forecasters are assumed to have no information regarding current innovations to productivity. Due to the frequency of GDP releases, our baseline VAR model is estimated on quarterly observations. In order to construct an alternative monthly measure of the nowcast error, we rely on industrial production and a survey of professional forecasters by Bloomberg regarding the growth of industrial production.¹⁸ Results are shown in the right panel of Figure 4. From a qualitative point of view, they are in line with those obtained for the baseline VAR model. Next we are turning to alternative assumptions regarding our sample and the number of lags included in the VAR model. Results are shown in Figure 5. The left panel shows results of the

¹⁸The Bloomberg survey forecasts are available for 1996M10 to 2012M12 and thus determine the sample period. The series on monthly hours is the index of aggregate weekly hours of production workers in manufacturing from the Bureau of Labor Statistics, while the corresponding growth rate of labor productivity is the difference in the growth rates of the volume index of industrial industrial production, from the Federal Reserve, and hours. The lag length is two years analog to the quarterly baseline specification.

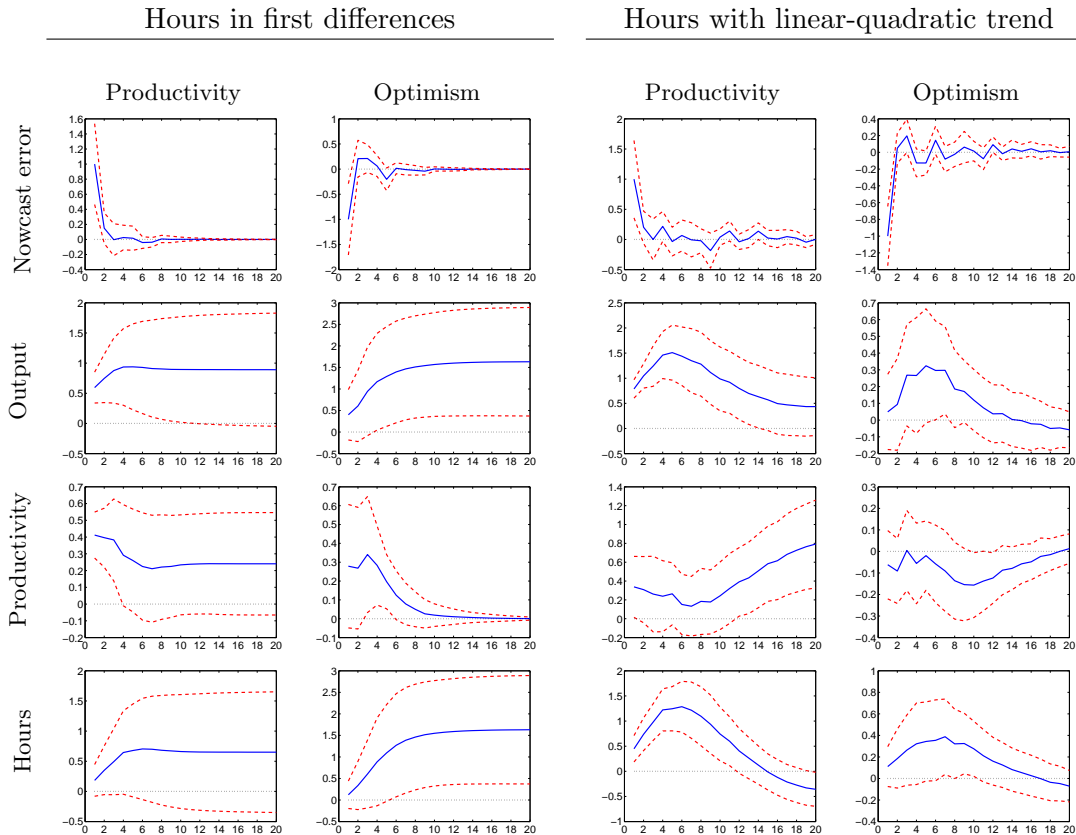


Figure 6: Impulse response functions to productivity and optimism shock: Sensitivity analysis III. Notes: left panel shows results for hours in first differences, right panel for hours after a linear quadratic trend has been removed.

long sample, i.e. 1968Q4–2012Q4. They are very similar to those of the baseline specification, see Figure 2. An exception is the response of labor productivity to the productivity shock which turns insignificantly negative after about six quarters. In the long-run (not shown), however, the response is positive as in the under the baseline. The right panel of Figure 5 shows the results for the model with four lags only. Again, results are fairly similar to the baseline specification, although we do not obtain a significant response of output to the optimism shock.

Finally, we explore the robustness of our results with respect to alternative assumptions regarding the trends in the time-series for hours worked. This issue has received considerably attention in the literature, as some studies found the trend specification crucial for the sign of the response of hours worked to a productivity shock based on long-run restrictions. We find that this not to be the case for our VAR model. Recall that we do not allow for a trend in hours in our baseline specification. Figure 6 shows results for a specifications where hours enter in first differences (left panel) and for a specification where a linear-quadratic trend has

been removed from hours worked (right panel).

5 Conclusion

In this paper we have developed a method to estimate the quantitative effects of optimism shocks, defined as wrong predictions of current fundamentals which do not move labor productivity in the long run. To motivate our empirical strategy and to justify our identification assumptions, we put forward a simple model which features optimism shocks alongside productivity shocks. On the basis of our estimated VAR model we find that optimism shocks account for up to 30% of output fluctuations.

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