Growth expectations, undue optimism, and short-run fluctuations*

Zeno Enders
University of Heidelberg
and CESifo

Michael Kleemann
Deutsche Bundesbank

Gernot J. Müller
University of Tübingen,
CEPR, and CESifo

July 2018

Abstract

We assess whether "undue optimism" (Pigou) contributes to business cycle fluctuations. In our analysis, optimism (or pessimism) pertains to fundamentals which determine economic activity in the long run. Optimism shocks are perceived changes of fundamentals that do not actually materialize. We develop a new strategy to identify optimism shocks in a VAR model. It is based on nowcast errors regarding current output growth, that is, the difference between actual growth and the real-time prediction of professional forecasters. We find that optimism shocks—in line with theory—generate a positive, but smaller than predicted, short-run output response. They account for up to 15 percent of output fluctuations.

Keywords: undue optimism, optimism shocks, noise shocks, animal spirits, business cycles, nowcast errors, VAR

JEL classification: E32

*Emails: zeno.enders@uni-heidelberg.de, michael.kleemann@bundesbank.de, and gernot.mueller@uni-tuebingen.de. The authors thank Jonas Arias, Olivier Blanchard, Olivier Coibion, Domenico Giannone, Lutz Kilian, Kristoffer Nimark, Franck Portier, Petr Sedláček, and participants in various seminars and conferences for helpful comments, as well as Kerstin Gärtner and Tobias Anger for research assistance. Part of this research was conducted while Enders was visiting the International Monetary Fund (IMF), the hospitality of which is gratefully acknowledged. Discussion papers represent the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank, the IMF or their staff.

1 Introduction

Do autonomous changes in expectations—changes of expectations that are not due to changes in fundamentals—cause 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 cause of "industrial fluctuations". Keynes' notion of "animal spirits" is a related, but distinct concept.[1] More recently, Beaudry and Portier (2004) explore the possibility of "Pigou cycles" in a quantitative business cycle model featuring possibly undue expectations regarding future fundamentals. Lorenzoni (2009) puts forward a model in which misperceptions regarding the current fundamentals ("noise shocks") turn out to be an important source of cyclical fluctuations.

In this paper, we take up the issue empirically. We estimate a vector autoregression (VAR) model on U.S. time-series data and seek to identify "optimism shocks", that is, changes in expectations due to a perceived change in fundamentals that does not actually materialize. While changes may be positive or negative ("pessimism shocks"), we refer to "optimism shocks" throughout. Blanchard et al. (2013) show that identification constitutes a formidable challenge in this case because optimism shocks are essentially mistakes of market participants. If, roughly speaking, we were able to detect such a mistake at a given point in time, so should market participants. Hence, there should be an immediate correction and no mistake to speak of in the first place. In light of these difficulties, one may resort to estimating full-fledged dynamic general equilibrium models in order to achieve identification (Barsky and Sims, 2012; Blanchard et al., 2013). This approach, however, is fairly restrictive as it imposes a lot of specific structure on the data.

In what follows, we maintain the less restrictive VAR framework, but develop a new identification strategy based on an informational advantage over market participants. Specifically, we show that it is possible to identify optimism shocks within a VAR model that includes an *ex post* measure of agents' misperceptions, namely the nowcast error regarding current output growth. We obtain the nowcast from the Survey of Professional Forecasters (SPF) and compute the nowcast error as the difference between actual output growth and the median of the predicted values in real time. A positive realization of the nowcast error implies that nowcasts have been too pessimistic. We emphasize that nowcast errors are a reduced-form measure which may reflect a variety of fundamental innovations.

[1] Keynes' animal spirits are "a spontaneous urge to action rather than inaction", which drive economic decisions beyond considerations based "on nothing but a mathematical expectation" (Keynes 1936, pp. 161–162).

The SPF is a widely recognized measure of private-sector expectations regarding the current state and prospects of the U.S. economy. It is also a frequently used benchmark to assess forecasting models (e.g., Giannone et al., 2008). Nevertheless, as we show in the first step of our analysis, nowcast errors can be sizeable. We also document that nowcast errors are positively correlated with economic activity and investigate how they respond to established measures of fundamental innovations. We find that a large number of innovations which have been identified in earlier studies do not systematically cause nowcast errors. This includes policy innovations, but also oil price and uncertainty shocks. In contrast, various measures of technology shocks impact nowcast errors significantly. Intuitively, because technology shocks are not directly observable in real time, market participants may be wrong about them or their impact. Hence, we think of optimism shocks as misperceptions of the rate of technological progress.

In the second step of our analysis, we show formally that it is possible to identify such optimism shocks on the basis of nowcast errors. We establish this result within a fairly standard business cycle model which is characterized by an informational friction that gives rise to nowcast errors. The model is a version of the dispersed-information model of Lorenzoni (2009), for which we are able to obtain closed-form solutions. The model solution has a VAR representation which features the nowcast error, labor productivity and hours worked. It permits us to recover optimism shocks, even if we consider a less stylized data generating process. In order to do so, we employ alternative identification strategies. Our baseline specification assumes that while nowcast errors are caused by either optimism shocks or technology shocks, only the latter influence labor productivity in the long run (Galí, 1999). Alternatively, we also permit other shocks to impact the nowcast error, but to a lesser extent than either optimism or technology shocks ("size restrictions"). Lastly, we also pursue further identification strategies based on sign restrictions.

Our main result is robust across identification schemes: while technology shocks raise both output and the nowcast error, optimism shocks raise output but lower the nowcast error. This finding is remarkable because the correlation of nowcast errors and output—unrestricted under our baseline identification scheme—changes from unconditionally positive to negative conditional on optimism shocks. Moreover, this negative comovement conforms well with the specific nature of optimism shocks: it is precisely because there is undue optimism and, hence, growth is overestimated, that economic activity expands—but less than expected. Thus a negative nowcast error obtains. We find that nowcast errors account for up to 15 percent of output fluctuations in the short run.

We stress that for optimism shocks to be reflected in nowcast errors, we require them to pertain to current productivity. This does not imply, however, that undue optimism is necessarily limited to the current period. Rather, market participants may expect productivity gains to be longer lasting or even permanent and indeed—as we document below—forecasts rarely shift independently of nowcasts. In our analysis, we do not capture the effects of undue optimism to the extent that it pertains to future fundamentals *only*. Including forecast errors in the VAR model is of little help in this regard, because they are also the result of fundamental innovations and policy reactions along the entire forecasting horizon. In order to identify "noisy news" rather than optimism shocks, one may instead resort to a dynamic rotation of the VAR's reduced-form residuals (Forni et al., 2017).

Conceptually, our analysis relates to a number of recent studies on the role of exogenous shifts in expectations as a source of business cycle fluctuations. Angeletos and La'O (2013) develop a model where "sentiment shocks" arise because market participants are unduly but simultaneously optimistic about their terms of trade. These shocks trigger aggregate fluctuations even if productivity is known to be constant. In a related contribution, Angeletos et al. (2017) rely on DSGE models in order to show that "confidence shocks", that is, autonomous variations in higher-order beliefs can account for salient features of the data. In earlier work, Milani (2011) introduces "expectation shocks" in a New Keynesian model with near-rational expectation formation. The model is estimated on U.S. data, including expectations data from the SPF. Expectation shocks are found to account for about half of the volatility of output.

A number of contributions have focused on the distinction between unexpected and anticipated technology shocks. Evidence from Beaudry and Portier (2006) suggests that business cycles are largely driven by expected future changes in productivity (see also Beaudry et al. 2011, Schmitt-Grohé and Uribe 2012, and Leduc and Sill 2013), while Barsky and Sims (2011) find the role of expected productivity innovations to be limited. To the extent that anticipated shocks do not materialize as expected, a recession might ensue (Jaimovic and Rebelo 2009).

Our analysis also relates to earlier studies that attempt to estimate the importance of optimism or sentiments for business cycle fluctuations. Blanchard (1993) provides an animal-spirits account of the 1990–91 recession, focusing on consumption. Carroll et al. (1994) show that consumer sentiment is a good predictor of consumption spending—aside from the information contained in other available indicators. Yet, in concluding, they suggest a "fundamental explanation" based on habits and precautionary saving motives.

Oh and Waldman (1990) show that "false macroeconomic announcements", identified as measurement errors in early releases of leading indicators, cause future economic activity. They refrain from a structural interpretation, however. Mora and Schulstad (2007) show that, once announcements regarding current growth are taken into account, the actual growth rate has no predictive power in determining future growth.

Finally, there is recent work that uses survey-based expectations data in order to show that incomplete information, imperfectly rational expectations or confidence may impact macroeconomic outcomes not only as an autonomous source but also by altering decision-making more generally. Nimark (2014) and Melosi (2017) develop and estimate dispersed-information models on data sets, which include inflation expectations as reported in the SPF. Both studies illustrate the potential of informational frictions in accounting for business cycle dynamics. Gennaioli et al. (2015) document that corporate investment is well explained by expectations data that, in turn, fail to satisfy a number of rationality tests. Bachmann and Sims (2012) show that consumer confidence amplifies the transmission of fiscal shocks in times of economic slack.

The remainder of the paper is structured as follows. The next section introduces our measure of nowcast errors and provides a number of descriptive statistics. Section 3 puts forward a simple theoretical model that allows us to clarify issues pertaining to the notion of optimism shocks and their identification. Section 4 presents the VAR model, our results, and an extensive sensitivity analysis. A final section concludes. The appendix provides more details on the theoretical model and reports results from a Monte Carlo exercise.

2 A reduced-form measure of misperceptions

In our analysis, we aim to uncover the effects of *optimism shocks*, that is, perceived technological progress that does not actually materialize. In this section, as a first step towards this end, we consider a reduced-form measure of misperceptions by computing *nowcast errors* regarding current U.S. output growth. Nowcast errors can be the result of optimism shocks, but they may also be due to fundamental, or "structural", innovations. Nowcast errors will play a key role in our identification strategy. In what follows, 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.

2.1 Data

Our main data source is the SPF, initiated by the American Statistical Association and the NBER in 1968Q4, now maintained at the Federal Reserve Bank of Philadelphia.[2] The SPF is a widely recognized measure of private-sector expectations regarding the current state and prospects of the U.S. economy. The survey is conducted on a quarterly basis. We focus on the forecast for output growth in the current quarter, that is, the nowcast. In this regard, it is important to note that panelists receive questionnaires at the end of the first month of the quarter and have to submit their answers by the second to third 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). At most, in order to nowcast output growth for the current quarter, forecasters may draw on the NIPA advance report regarding output in the previous quarter.[3] Predicted quarterly output growth is annualized and measured in real terms. Note that, initially, within the SPF, output is measured by GNP, later by GDP.[4]

As a first pass at the data, Figure 1 illustrates how nowcasts relate to forecasts, using data for the period 1969Q1–2014Q4. The left panel plots the revision of the median nowcast against the revision of the median one-quarter-ahead forecast.[5] Revisions are positively correlated and often of comparable magnitude. The correlation is 0.47 and significant at the 1%-level. The right panel exploits the cross section of the data set. It shows the fraction of professional forecasters who revise forecasts for future output growth—one, two, and three quarters ahead, respectively. We indicate in red the fraction of forecasters who simultaneously revise forecasts and nowcasts. Blue markers, in turn, depict the fraction of forecast revisions that take place while nowcasts remain unchanged. The later instances are fairly rare in our sample. Overall, we find evidence that is consistent with the view that

[2] Professional forecasters are mostly private financial-sector firms. The number of participating institutions 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 2014Q4, 42 forecasters participated in the survey.

[3] In a robustness exercise below, we use monthly (survey) data on expectations for industrial production. In this case, participants can adjust their nowcast until the official data release shortly after the end of the month.

[4] For the SPF forecasts of GNP/GDP, we use the series DRGDP2, which we obtain from the Real-time Data Research Center of the Philadelphia Fed. This series corresponds to the median nowcast of the quarterly growth rate of real output, seasonally adjusted at annual rates (real GNP prior to 1992 and real GDP afterwards). Prior to 1981Q3, the SPF asks for nominal GNP only. In this case, the implied forecast for real GNP is computed on the basis of the nowcast for the price index of GNP.

[5] The revision of the nowcast is the difference between the estimate in period t and the estimate in period $t-1$ of output growth in period t. Correspondingly, the revision of the forecast for output growth in period $t+1$ is the change in the estimate between periods $t-1$ and t.

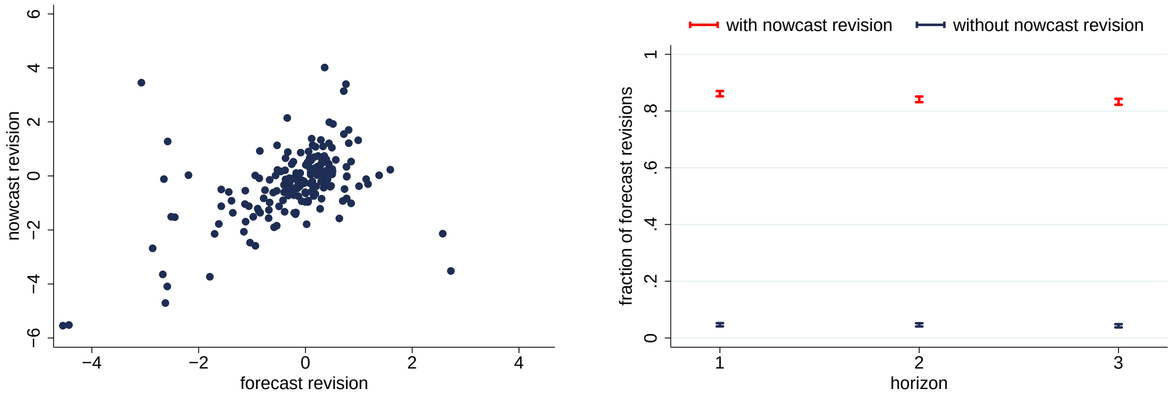

Figure 1: Revisions of nowcasts and forecasts. Left panel plots revision of median nowcast (vertical axis) against revision of one-quarter-ahead median forecast (horizontal axis), measured in annualized percentage points. Right panel: frequency of forecast revisions across individual forecasters (for forecasting horizons t+1 to t+3); red: forecasters revise nowcast and forecast simultaneously; blue: forecasters revise forecast, but not nowcast; whiskers represent 95%-confidence intervals.

expectations about output growth tend to shift simultaneously across the entire forecasting horizon under consideration. This includes, in particular, the nowcast for current output growth.

Our analysis below is based on nowcast *errors*. We compute it as the difference between the survey's median nowcast and the actual value reported later by the BEA. We use the median nowcast error over all forecasters, as it is less prone to outliers than the mean error. Also, nowcast errors based on the mean rather than the median exhibit a somewhat higher variance. Our main results, however, are unchanged once we use the mean nowcast error. We compute two measures of nowcast errors based on the advance and the final estimate for actual output growth, which correspond to the BEA's first and third data release. We thereby address concerns that the assessment of nowcasts or, more generally, forecasts depends on what is being used as "actual" or realized values (see, for example, Stark and Croushore 2002).[6] Throughout we refer to nowcast errors as either "based on first-release" on "based on final-release" data. Note that our final-release-based measure is computed on data prior to further comprehensive and benchmark revisions of the data, which take place at a later date.[7]

[6]In fact, the authors consider a set of alternative definitions of actuals and find statistically significant differences in forecast evaluations for real output. We show below, however, that our results hold irrespective of the choice of first or final-release data.

[7]Benchmark revisions take place approximately every five years. Comprehensive revisions are more frequent and may also be quite substantial concerning, for instance, the classification of R&D expenditure.

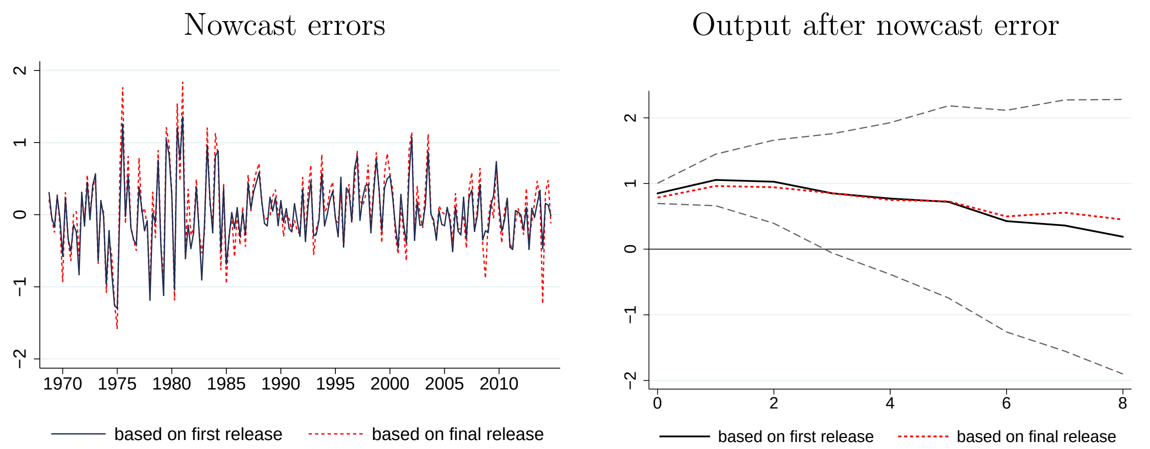

Figure 2: Nowcast errors. Left panel: series based on first-release data (solid lines) and final-release data (dashed lines). Errors are measured in annualized percentage points (vertical axis). Right panel: cumulative impulse response of output growth to a nowcast error based on local projections. Horizontal axis measures quarters; vertical axis measures percentage deviation of output from the average growth path. Dashed lines indicate 90%-confidence bounds implied by Newey-West standard errors.

2.2 Nowcast errors

The left panel of Figure 2 shows the time series of nowcast errors, measured in annualized percentage points. The solid and dashed lines represent results based on first and final-release data, respectively. Although the two series comove strongly (correlation: 0.94), there are perceptible differences. For instance, there are sizeable negative errors in the second half of 2008 only for the measure based on the final release. 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 to what initial data suggested. The same holds true for 2012Q4, as the U.S. economy approached its so-called fiscal cliff. Instead, during the first half of the sample, errors based on first-release data are shifted somewhat downward relative to those based on final-release data.

We provide summary statistics for both time series in Table 1. The mean nowcast error is not significantly different from zero. The standard error and the largest realizations of the nowcast error are somewhat larger in the case of final-release data. Finally, the last two columns of Table 1 report results of a Ljung–Box test, suggesting that there is no serial correlation in neither series.[8] Hence, in this regard, nowcast errors differ markedly

[8]We also reject the hypothesis that there is first or higher-order serial correlation if tested individually for each lag length up to 12 lags.

Table 1: Summary statistics for nowcast errors

						Ljung–Box test	
	N	Mean	SD	Min	Max	Q-stat.	p-value
Final release	185	0.058	0.539	-1.585	1.843	12.048	0.442
First release	185	0.022	0.457	-1.299	1.358	10.716	0.553

Notes: Nowcast errors computed on the basis of final release (top) and first release (bottom), measured in percentage points; sample: 1968Q4–2014Q4. Means are tested against zero based on a standard t-test. For both series, $H_0 = 0$ cannot be rejected at the 10%-level. The last two columns report Q-statistics and p-values for a Ljung-Box test assessing the null hypothesis of zero autocorrelations up to 12 lags.

from forecast errors, which tend to exhibit considerable persistence as established in earlier work by Zarnowitz (1985).[9] Also, recent work by Coibion and Gorodnichenko (2012, 2015) shows that forecast errors adjust only sluggishly to new information. We discuss below how our results on nowcast errors relate to theirs.

What causes nowcast errors? Assuming that the median forecaster has a correct understanding of the economy, structural innovations that are public information should not induce systematic errors.[10] On the other hand, structural innovations that are not directly observable by market participants are likely to generate nowcast errors. To assess this hypothesis, we investigate whether popular (and relatively uncontroversial) series of structural innovations impact the nowcast error. Specifically, we consider the following shock measures: neutral and investment specific technology shocks as identified in Fisher (2002, 2006), innovations in total factor productivity compiled by Fernald (2014), monetary policy shocks identified by Romer and Romer (2004) and extended by Coibion et al. (2017), or estimated by Nakamura and Steinsson (2018), uncertainty shocks of Bloom (2009), macroeconomic uncertainty shocks measured by Jurado et al. (2015), defense spending shocks identified by Ramey (2014), tax shocks estimated by Romer and Romer (2010), and oil supply shocks from Kilian (2008).[11]

[9]He finds that serial correlation in forecast errors tends to increase with the forecasting horizon for many macroeconomic variables in the SPF. In addition, serial correlation seems to be most prevalent in inflation forecasts, generating a large body of literature on the topic, while evidence for GDP forecasts is rather mixed.

[10]In this context, systematic errors would imply that, on average, forecasters keep on making the same error after specific observable shocks.

[11]We obtain the Fisher-type shocks by estimating a Fisher-type VAR based on the relative price of investment, per capita output, and hours per capita. Total factor productivity innovations correspond to the series (dtfp) derived by Fernald (2014). In the case of monetary policy, we use the quarterly average of

Table 2: Nowcast errors and fundamental innovations

Structural innovation	Sample	Nowcast error	Concurrent-effect Coeff.	SE	Granger-causality yes/no	prob. > F
Neutral technology	1968-2014	final	0.258***	(0.075)	yes	(0.041)
Fisher type		first	0.245***	(0.074)	yes	(0.089)
Investment-specific techn.	1968-2014	final	0.452***	(0.074)	yes	(0.005)
Fisher type		first	0.419***	(0.089)	yes	(0.000)
Total factor productivity	1968-2014	final	0.499***	(0.065)	yes	(0.067)
Fernald (2014)		first	0.461***	(0.067)	yes	(0.061)
Monetary Policy	1968-2008	final	0.127	(0.137)	no	(0.643)
Romer & Romer (2004)		first	0.122	(0.138)	no	(0.709)
Monetary Policy	2000-2014	final	-0.089	(0.127)	no	(0.649)
Nakamura & Steinsson (2018)		first	-0.109	(0.101)	no	(0.873)
Uncertainty	1968-2008	final	0.039	(0.074)	no	(0.234)
Bloom (2009)		first	0.026	(0.077)	no	(0.250)
Macro Uncertainty	1968-2014	final	-0.093	(0.102)	no	(0.281)
Jurado et al. (2015)		first	-0.094	(0.102)	no	(0.216)
Defense Spending	1968-2013	final	0.086	(0.075)	no	(0.193)
Ramey (2014)		first	0.064	(0.064)	no	(0.186)
Taxes	1968-2007	final	-0.099	(0.123)	no	(0.427)
Romer & Romer (2010)		first	-0.089	(0.120)	no	(0.516)
Exogenous Oil Supply	1971-2004	final	-0.023	(0.059)	no	(0.633)
Kilian (2008)		first	-0.057	(0.061)	no	(0.574)

Notes: Concurrent impact effect on nowcast error obtained from regression of nowcast error on concurrent structural innovations (standardized regression coefficients); regressions include four lags of the nowcast error; Newey-West standard errors robust for auto-correlation up to four lags are reported in parentheses; Granger-causality tests based on bi-variate vector auto-regressions of structural innovations and nowcast errors; Number of lags set according to AIC; in case of residual auto-correlation, more lags are included.

the monthly shock series (RESID) of Romer and Romer (2004) as extended by Coibion et al. (2017) and of the high frequency measure (FFR_shock) identified by Nakamura and Steinsson (2018), respectively. In case of the former, we also include dummies to control for the impact of the Volcker dis-inflation period, given that Coibion (2012) finds that the two episodes 1980Q2 and 1980Q4, which are showing the strongest shocks, are likely to be particularly noisy for measuring policy innovations and to drive the results of Romer and Romer (2004). Regarding uncertainty shocks, we rely on the quarterly average of the monthly series of stock-market-volatility shocks identified in the baseline VAR of Bloom (2009) and of macroeconomic uncertainty for $h = 3$ months ahead as measured by Jurado et al. (2015), respectively. The defense news identified by Ramey (2014) are the present-value changes in expected defense spending due to political

In order to investigate which of these shocks cause nowcast errors, we regress the nowcast in each instance on the contemporaneous realization of the structural shock while also including four lags of the nowcast error in the regression model. We standardize regression coefficients such that they represent the nowcast error associated with a one-standard-deviation innovation in the shock series. In a second experiment, we also assess whether there is Ganger causality by running a bi-variate VAR in the series of the shock and the nowcast error. In this case we determine the lag length according to the AIC criterion, except if residuals are autocorrelated, in which case we include additional lags until the autocorrelation vanishes, up to 12 lags. Finally, we compute Wald statistics and test the hypothesis that all coefficients on the lags of the known shock series are jointly zero in the equation for the nowcast error. The sample varies across shock series, since we use the longest overlapping sample in each case.

Table 2 reports results for both final and first release data. Newey-West standard errors are displayed in parentheses. The rightmost column reports probability levels for the null hypothesis of no Granger causality based on small-sample F statistics. We find that technology shocks impact nowcast errors significantly. Moreover, there is also evidence for Granger causality. This holds true for the technology shocks identified à la Fisher, but also for Fernald's TFP measure. The results reported in the table are based on the maximum sample of Fernald's measure (dtfp), which is not adjusted for factor utilization. For the sample that we use in our VAR below, also the adjusted TFP innovations (dtfp_util) have a significant effect on the nowcast error. Additionally, they Granger-cause the nowcast error in this case.

The results for the non-technology innovations are fundametally different. The effects are much smaller and insignificant throughout. There is also no evidence for Granger causality. In sum, we find that professional forecasters tend to understand the effect of structural innovations on economic activity rather well. There is no evidence for systematic mistakes.[12] An important exception are technology shocks: they have a significant effect

events scaled by lagged nominal GDP. For tax shocks, we use the quarterly average of the monthly shock series "sum of deficit-driven and long-run tax changes" (EXOGENRRATIO) of Romer and Romer (2010). The series of exogenous oil supply (oilshock) is based taken from Kilian (2008).

[12]Coibion and Gorodnichenko (2012) find that mean forecast errors of inflation respond persistently to shocks. In order to resolve an apparent conflict with our results regarding non-technology shocks, we make two observations. First, we are interested in output growth rather than inflation. In a related paper, Coibion and Gorodnichenko (2015) consider to what extent current forecast revisions predict forecast errors. In a univariate context, the contribution of forecast revisions (averages over all considered horizons; sample: 1968–2014) appears to be strongly significant for inflation, but not significant in the case of output growth. Second, we focus on nowcast rather than on forecast errors. It is thus important to recognize that

on nowcast errors, both statistically and economically. Specifically, technology innovations tend to raise the nowcast error contemporaneously, that is, they tend to raise the growth of economic activity beyond the expected level.

2.3 Nowcast errors and economic activity

Nowcast errors are positive surprises regarding current activity. They are also positively correlated with output growth.[13] To explore systematically how current nowcast errors relate to economic activity, we estimate the dynamic relationship on the basis of local projections (Jordà, 2005). In particular, we relate current and future output growth to current nowcast errors.

The right panel of Figure 2 shows the cumulative impulse response function of output growth to a nowcast error. The horizontal axis measures quarters, the vertical axis percentage deviation of output from the average growth path. Dashed lines indicate 90%-confidence bounds implied by Newey-West standard errors.[14] We find that nowcast errors predict a strong, mildly hump-shaped increase in economic activity. The effect is initially a bit stronger for our measure based on first-release data, yet differences are generally very moderate. The finding that (reduced-form) nowcast errors predict future activity to increase is particularly noteworthy in light of our estimates regarding the effects of optimism shocks documented in Section 4 below. In the following section, we put forward a model to explore the link between optimism shocks and nowcast errors more systematically.

3 Optimism shocks: Theory

In our empirical analysis we impose as little structure as possible on the data in order to identify optimism shocks. Yet, by way of example, we now put forward a specific model that allows us to formally define optimism shocks, discuss conditions under which they may affect economic activity, and clarify issues pertaining to identification. The model captures in a stylized way the informational friction that gives rise to nowcast errors. Lorenzoni

professional forecasters tend to adjust forecasts rather smoothly (Nordhaus 1987). Indeed, Coibion and Gorodnichenko (2015) find that, while forecast revisions tend to predict forecast errors (averages over all considered variables), the effect is only marginally significant for nowcast errors.

[13]The correlation between GDP growth and the nowcast error is 0.51 and 0.47 for the final-release measure and first-release measure, respectively.

[14]The error structure is assumed to be possibly heteroskedastic and autocorrelated up to lag 4. We also include four lags of GDP growth in the regression.

(2009) and Coibion and Gorodnichenko (2012) find that models of information rigidities in general, and of noisy information in particular, are successful in predicting empirical regularities of survey data on expectations.

Our model thus builds on the noisy and dispersed information model of Lorenzoni (2009). As our goal is to derive robust qualitative predictions, we simplify the original model, notably by assuming predetermined rather than staggered prices. As a result, it is possible to solve an approximate model in closed form. A key feature of the model is that agents do not observe output at the time of decision-making. Importantly, the econometrician's information set differs in this regard, because aggregate output, and hence a measure of the nowcast error, becomes available ex post. This difference is crucial in terms of identification as we show below.

3.1 Setup and timing

There is a continuum of islands (or locations), indexed by $l \in [0, 1]$, each populated by a representative household and a unit mass of producers, indexed by $j \in [0, 1]$. Each household buys from a subset of all islands, chosen randomly in each period. Specifically, it buys from all producers on n islands included in the set $\mathcal{B}_{l,t}$, with $1 < n < \infty$.[15] Households have an infinite planning horizon. Producers produce differentiated goods on the basis of island-specific productivity, which is determined by a permanent, economy-wide component and a temporary, idiosyncratic component.[16] Both components are stochastic. Financial markets are complete such that, assuming identical initial positions, wealth levels of households are equalized at the beginning of each period.

The timing of events is as follows: each period consists of three stages. During stage one of period t, information about all variables of period $t-1$ is released. Subsequently, nominal wages are determined and the central bank sets the interest rate based on expected inflation.

Shocks emerge during the second stage. We distinguish between shocks that are directly observable and shocks that are not. Optimism and technology shocks are not directly observable in the following sense: information about idiosyncratic productivity is private to each producer, but, in addition, all agents observe a signal about average productivity.

[15] This setup ensures that households cannot exactly infer aggregate productivity from observed prices. At the same time, individual producers have no impact on the price of households' consumption baskets.

[16] As argued by Lorenzoni (2009), this setup can account for the empirical observations that the firm-level volatility of productivity is large relative to aggregate volatility and that individual expectations are dispersed.

While the signal is unbiased, it contains an i.i.d. zero-mean component: the optimism shock. We allow for one generic shock that is observable. To simplify the discussion, we refer to this shock as a "monetary policy shock" with the understanding that other observable shocks would play a comparable role in terms of identification. Given these information sets, producers set prices.

During the third and final stage, households split up. Workers work for all firms on their island, while consumers allocate their expenditures across differentiated goods based on public information, including the signal, and information contained in the prices of the goods in their consumption bundle. Because the common productivity component is permanent and households' wealth and information are equalized in the next period, agents expect the economy to settle on a new steady state from period $t+1$ onwards.

3.2 Households

A representative household on island l ("household l", for short) maximizes lifetime utility, given by

$$U_{l,t} = E_{l,t} \sum_{k=t}^{\infty} \beta^{k-t} \ln C_{l,k} - \frac{L_{l,k}^{1+\varphi}}{1+\varphi} \qquad \varphi \geq 0, \quad 0 < \beta < 1,$$

where $E_{l,t}$ is the expectation operator based on household l's information set at the time of its consumption decision in stage three of period t (see below). $C_{l,t}$ denotes the consumption basket of household l, while $L_{l,t}$ is its labor supply. The flow budget constraint is given by

$$E_t \varrho_{l,t,t+1} \Theta_{l,t} + B_{l,t} + \sum_{m \in \mathcal{B}_{l,t}} \int_0^1 P_{j,m,l,t} C_{j,m,l,t} dj \leq \int_0^1 \Pi_{j,l,t} dj + W_{l,t} L_{l,t} + \Theta_{l,t-1} + (1+r_{t-1}) B_{l,t-1},$$

where $C_{j,m,l,t}$ denotes the amount bought by household l from producer j on island m and $P_{j,m,l,t}$ is the price for one unit of $C_{j,m,l,t}$. At the beginning of the period, the household receives the payoff $\Theta_{l,t-1}$, given a portfolio of state-contingent securities purchased in the previous period. $\Pi_{j,l,t}$ are the profits of firm j on island l and $\varrho_{l,t,t+1}$ is household l's stochastic discount factor between t and $t+1$. The period-t portfolio is priced conditional on the (common) information set of stage one, hence we apply the expectation operator E_t. $B_{l,t}$ are state non-contingent bonds paying an interest rate of r_t. The complete set of state-contingent securities is traded in the first stage of the period, while state-non-contingent bonds can be traded via the central bank throughout the entire period. The interest rate of the non-contingent bond is set by the central bank. All financial assets are in zero net supply. The bundle $C_{l,t}$ of goods purchased by household l consists of goods sold in a subset of all islands in the economy

$$C_{l,t} = \left(\frac{1}{n} \sum_{m \in \mathcal{B}_{l,t}} \int_0^1 C_{j,m,l,t}^{\frac{\gamma-1}{\gamma}} dj \right)^{\frac{\gamma}{\gamma-1}} \qquad \gamma > 1.$$

While each household purchases a different random set of goods, we assume that the number n of islands visited is the same for all households. The price index of household l is therefore

$$P_{l,t} = \left(\frac{1}{n} \sum_{m \in \mathcal{B}_{l,t}} \int_0^1 P_{j,m,l,t}^{1-\gamma} dj \right)^{\frac{1}{1-\gamma}}.$$

3.3 Producers and monetary policy

The central bank follows an interest-rate feedback rule but sets r_t before observing prices, that is during stage one of period t:

$$r_t = \psi E_{cb,t} \pi_t + \nu_t \qquad \psi > 1,$$

where π_t is economy-wide net inflation, calculated on the basis of all goods sold in the economy. The expectation operator $E_{cb,t}$ is conditional on the information set of the central bank. This set consists of information from period $t-1$ only, that is, the central bank enjoys no informational advantage over the private sector.[17] ν_t is a monetary policy shock that is observable by producers and households alike.

Producer j on island l produces according to the following production function

$$Y_{j,l,t} = A_{j,l,t} L_{j,l,t}^{\alpha} \qquad 0 < \alpha < 1,$$

featuring labor supplied by the local household as the sole input. $A_{j,l,t} = A_{l,t}$ denotes the productivity level of producer j, which is the same for all producers on island l. During stage two, the producer sets her optimal price for the current period. Given prices, the level of production is determined by demand during stage three.

[17] Pre-set prices and interest rates allow us to discard the noisy signals about quantities and inflation observed by producers and the central bank in Lorenzoni (2009), simplifying the signal-extraction problem without changing the qualitative predictions of the model. Pre-set wages, on the other hand, guarantee determinacy of the price level. They do not affect output dynamics after optimism and technology shocks, because goods prices may still adjust in the second stage of the period.

3.4 Productivity and signal

Log-productivity on each island is the sum of an aggregate and an island-specific idiosyncratic component

$$a_{l,t} = x_t + \eta_{l,t},$$

where $\eta_{l,t}$ is an i.i.d. shock with variance σ_η^2 and mean zero. It aggregates to zero across all islands. The aggregate component x_t follows a random walk

$$\Delta x_t = \varepsilon_t.$$

The i.i.d. productivity shock ε_t has variance σ_ε^2 and mean zero. During stage two of each period, agents observe a public signal about x_t. This signal takes the form

$$s_t = \varepsilon_t + e_t,$$

where e_t is an i.i.d. optimism shock with variance σ_e^2 and mean zero. Producers also observe their own productivity. Hence, their expectations of Δx_t are

$$E_{j,l,t}\Delta x_t = \rho_x^p s_t + \delta_x^p (a_{j,l,t} - x_{t-1}),$$

with $E_{j,l,t}$ being the expectation of producer j on island l when setting prices (in stage two). The coefficients ρ_x^p and δ_x^p are the same for all producers, where these and the following ρ and δ-coefficients are functions of the structural parameters that capture the informational friction. They are non-negative and smaller than unity; see Appendix A. Finally, while shopping during stage three, consumers observe a set of prices. Given that they have also observed the signal, they can infer the productivity level of each producer in their sample. Consumers' expectations are thus given by

$$E_{l,t}\Delta x_t = \rho_x^h s_t + \delta_x^h \tilde{a}_{l,t},$$

where $\tilde{a}_{l,t}$ is the average over the realizations of $a_{m,t} - x_{t-1}$ for each island m in household l's sample. ρ_x^h and δ_x^h are equal across households. The model nests the case of complete information about all relevant variables for households and producers if $\sigma_e^2 = 0$. If $\sigma_e^2 > 0$, producers will set prices based on potentially overly optimistic or pessimistic expectations of productivity. Consumers also have complete information if $n \to \infty$.

3.5 Market clearing

Goods and labor markets clear in each period:

$$\int_0^1 C_{j,m,l,t} dl = Y_{j,m,t} \ \ \forall j, m \qquad L_{l,t} = \int_0^1 L_{j,l,t} dj \ \ \forall l,$$

where $C_{j,m,l,t} = 0$ if household l does not visit island m. The asset market clears in accordance with Walras' law.

3.6 Results

We derive a solution of the model based on a linear approximation to the equilibrium conditions around the symmetric steady state; see Appendix A for details. Lower-case letters denote percentage deviations from steady state. We obtain the following propositions for which we provide proofs in Appendix B.

Proposition 1 *A positive optimism shock ($e_t > 0$), a positive productivity shock ($\varepsilon_t > 0$), and a negative monetary policy shock ($\nu_t < 0$) raise output. Formally, we have*

$$y_t = x_{t-1} + \underbrace{\rho_x^h(1-\Omega)}_{>0} e_t + \underbrace{\left[(\delta_x^h + \rho_x^h)(1-\Omega) + \Omega\right]}_{>0} \varepsilon_t \underbrace{- \frac{\alpha}{\alpha + \psi(1-\alpha)}}_{<0} \nu_t,$$

with $0 < \Omega = \frac{n - \delta_x^h(1-\alpha)[(n-1)\delta_x^p + 1]}{n\alpha + (1-\alpha)\left\{(1-\delta_x^h)[1+\delta_x^p(n-1)] + (n-1)\gamma(1-\delta_x^p)\right\}} < 1.$

Proposition 2 *A positive optimism shock induces a negative nowcast error, while a positive productivity shock induces a positive nowcast error. This holds for nowcast errors of producers and households alike. Monetary policy shocks do not cause nowcast errors. Formally,*

$$y_t - E_{k,t} y_t = \underbrace{-\rho_x^k \left[\delta_x^h(1-\Omega) + \Omega\right]}_{<0} e_t + \underbrace{\left[\delta_x^h(1-\Omega) + \Omega\right](1 - \delta_x^k - \rho_x^k)}_{>0} \varepsilon_t,$$

with $E_{k,t}$ standing for either $E_{j,l,t}$ or $E_{l,t}$, and ρ^k, δ^k correspondingly for ρ^p, δ^p or ρ^h, δ^h.

Hence, productivity and optimism shocks raise actual output but also lead to output misperceptions. Consider first the optimism shock. Producers expect aggregate productivity to be high—resulting in higher demand—but also observe that their own productivity is unchanged, which they attribute to a negative realization of the idiosyncratic productivity component. Consequently, they raise prices above what they expect the average price level to be. However, due to strategic complementarities in price-stetting, the deviation from the expected average price level is subdued. Consumers, in turn, observe higher prices besides the public signal. They, too, attribute this increase to adverse temporary productivity shocks suffered by those particular firms from which they buy. This allows households to entertain the notion of higher aggregate productivity and future income. They thus raise expenditures despite the observed price increase and, hence, economic activity expands.[18] Yet, as each producer and each household considers itself unlucky relative to its peers, current output is actually lower than expected: a negative nowcast error obtains.

After a productivity shock, producers also do not fully trust the signal about the aggregate component and attribute some of the increased productivity to idiosyncratic factors. They therefore reduce prices below what they expect the average price level to be. Consumers, in turn, observe lower prices and expect higher income. They consequently raise consumption. However, both producers and their customers expect other producers to set higher prices and consequently underestimate actual output. A positive nowcast error obtains.

Finally, we stress that monetary policy shocks have no impact on nowcast errors. More generally, any other shock that enters the information set of households and producers will not generate nowcast errors, as both are aware of the economic environment and, hence, the effect of shocks. Misperceptions about economic activity thus arise only after imperfectly observed shocks, such as innovations in productivity, or optimism shocks.

3.7 VAR representation

In addition to clarifying the nature of optimism shocks, the model allows us to address concerns about whether optimism shocks can be uncovered at all on the basis of an estimated VAR model. In this regard, the set of actual time series used in the estimation is crucial. Noting that we estimate our VAR in Section 4 on time series for nowcast errors, labor productivity, and hours worked, that is, on the following vector

$$\tilde{Y}_t' = \left[\begin{array}{ccc} \Delta y_t - E_{k,t}\Delta y_t & \Delta(y_t - l_t) & l_t \end{array} \right],$$

we obtain the following proposition.

[18] As pointed out by Lorenzoni (2009), the optimism shock provides a possible microfoundation for the traditional concept of a demand shock: agents are too optimistic about economic fundamentals, resulting in unusually high demand.

Proposition 3 *Given $\tilde{Y}_t$, the dynamics of the model can be represented by a VAR(1):*

$$\tilde{Y}_t = A\tilde{Y}_{t-1} + B\tilde{V}_t,$$

where

$$\tilde{V}_t' = \begin{bmatrix} \varepsilon_t & e_t & \nu_t \end{bmatrix}$$

contains shocks to aggregate productivity, optimism, and monetary policy. The matrices A and B are given in the proof (see Appendix B).

Intuitively, we are able to cast the model dynamics in VAR form because we rely on variables that are not contemporaneously observed by agents in the model. Specifically, we make use of the fact that we as econometricians can observe aggregate time series, which are released with a lag and hence not observable (by the agents in the model) in real time. If, instead, one were to restrict the VAR to contain variables observed by agents in real time, the model would generally not be invertible. Proposition 3 is thus consistent with the result of Blanchard et al. (2013), according to which optimism shocks cannot be recovered from actual time-series data by an econometrician who has no informational advantage over market participants. Yet, as documented in Section 2, actual nowcast errors regarding output growth can be sizable. To the extent that they can be measured *ex post*, they allow us to identify optimism shocks.

Finally, the model also provides us with specific identification restrictions, which we impose on the VAR model below. Given matrices A and B, we obtain the following corollary.

Corollary 1 *Monetary policy shocks have no impact on the nowcast error, neither in the short nor the long run. Furthermore, optimism shocks do not alter labor productivity in the long run.*

Our results are based on a model that is deliberately stylized. We therefore use Monte Carlo methods to check the validity of our identification strategy for a richer setup. For this purpose, we use Lorenzoni's original model as the data-generating process. It features richer dynamics because of staggered price-setting. Figure C.1 in the appendix shows the results. Given the vector of observables $\tilde{Y}_t'$ as well as our identification assumptions stated below, we find that the VAR performs well, although there is a tendency in small samples to somewhat underestimate the effects of both technology and optimism shocks.

4 Optimism shocks: Evidence

We are now in a position to identify the effects of optimism shocks in actual time-series data and to quantify their contribution to short-run fluctuations. For this purpose, we estimate a VAR model on U.S. data. It includes—as the key to our identification strategy—a time series of realized nowcast errors. As it is available ex post only, we have an informational advantage over market participants and are able to identify autonomous shifts in optimism or pessimism. Our baseline identification strategy combines short and long-run restrictions. Yet, as we document in Section 4.3 below, our main result also obtains under alternative identification strategies for which we relax, in turn, each of the restrictions imposed in the baseline.

4.1 VAR specification and identification

Our point of departure is the VAR model put forward by Galí (1999) in order to identify the effects of technology shocks. It features, in addition to the growth rate of labor productivity and (the log of) hours worked, the nowcast error computed on the basis of first-release data.[19] Formally, as we collect these variables in the vector $\tilde{Y}_t$, we can represent the VAR model in reduced form as follows:

$$\tilde{Y}_t = \sum_{i=1}^{L} A_i \tilde{Y}_{t-i} + u_t. \tag{4.1}$$

Here, L is the number of lags and u_t is a vector of potentially mutually correlated innovations with covariance matrix $\Omega = Euu'$. We also include a constant and a linear-quadratic time trend in the VAR model.[20]

We estimate the model on quarterly data covering the period 1983Q1–2014Q4. While our measure of nowcast errors has been available since the late 1960s (see Section 2), we disregard observations prior to 1983 because the U.S. business cycle was subject to considerable changes in the early 1980s, possibly due to a change in the conduct of monetary policy (Clarida et al. 2000; McConnell and Perez-Quiros 2000). In our sensitivity analysis, we show that results for the full sample are not significantly different from those for the baseline sample. The same is true for a sample that ends before the financial crisis.

[19] Labor productivity is output per hour of all persons in the business sector. The data source is the Bureau of Labor Statistics (BLS).

[20] See the discussion in Francis and Ramey (2005) and Galí and Rabanal (2005). Below, we consider alternative trend specifications to address the potential non-stationarity of the time series for hours worked.

Regarding the number of lags L, we account for concerns about a lag-truncation bias. Chari et al. (2008) show that it is particularly severe if long-run restrictions are imposed in VAR models. Hence, we set $L = 12$ in the baseline specification. This value also ensures that our residuals do not display autocorrelation, which is present for smaller values of L.[21] We consider alternative specifications with fewer lags in our sensitivity analysis below.

Turning to identification, assume that $\tilde{Y}_t$ includes from top to bottom, the nowcast error, labor productivity, and hours worked. Additionally, let ε_t^{tech} denote a technology shock, ε_t^{opt} an optimism shock and ε_t^{unlab} a third shock to which we do not attach any structural interpretation (the "unlabeled shock"). We stack the shocks in the following vector:

$$\varepsilon_t = \begin{bmatrix} \varepsilon_t^{tech} \\ \varepsilon_t^{opt} \\ \varepsilon_t^{unlab} \end{bmatrix}, \text{ where } u_t = B\varepsilon_t \text{ and } E\varepsilon\varepsilon' = I. \tag{4.2}$$

In order to identify matrix B, given estimates of matrices Ω and A_i, we impose three zero restrictions on the impact matrix B and the long-run matrix A_0:

$$B = \begin{bmatrix} * & * & 0 \\ * & * & * \\ * & * & * \end{bmatrix}, \quad A_0 \equiv \left(I - \sum_{i=1}^{L} A_i \right)^{-1} B = \begin{bmatrix} * & * & 0 \\ * & 0 & * \\ * & * & * \end{bmatrix}. \tag{4.3}$$

Intuitively, the key to our identification strategy is the assumption that nowcast errors are only due to either technology or optimism shocks, both in the short and the long run. This is captured formally by the zero restrictions in the upper-right of matrices B and A_0. In addition, we impose a zero restriction in the second row of the long-run matrix A_0. Below we perform an extensive sensitivity analysis where we relax each identification restriction in turn. In this analysis we also permit, for instance, other shocks to impact the nowcast error and, in addition, estimate our model on monthly observations in which case restrictions are less limiting. For now, however, we provide a rationale for the identification restrictions that we impose in the baseline.

First, the restriction on the impact matrix B reflects the assumption that the median professional forecaster does not systematically misjudge the effect of structural disturbances on the economy, except in case of technology shocks. Importantly, this does not require

[21] Here, we rely on a Lagrange-multiplier test (Johansen, 1995). Moreover, Monte Carlo evidence suggests that a higher number of lags reduces the lag-truncation bias considerably (De Graeve and Westermark, 2013). Also note that too parsimonious specifications risk underestimating the true dynamics of the population process and are characterized by spuriously tight confidence intervals (Kilian, 2001).

forecasters to correctly predict the effect of *all* non-technology shocks. For, under our identification scheme, optimism shocks may occur simultaneously (albeit unsystematically) with unlabeled shocks: the occasional misperception of a non-technology shock represents an optimism shock as well. In addition, we note that while the restriction on the impact matrix B is in line with the model put forward in the previous section (Corollary 1), its plausibility extends beyond a specific model. In Section 2 above, we show that with the exception of TFP innovations, a large number of identified shocks do not affect nowcast errors significantly. This is not a proper test of our identification assumption, since the evidence established in Section 2 rests, if only implicitly, on the identification assumptions employed by earlier studies. Still, the evidence is highly suggestive and consistent with our identification assumption.[22]

Second, to appreciate the restriction on the long-run matrix A_0, note that it constrains the *cumulative* response of nowcast errors to the unlabeled shock to be zero. In the theoretical model developed above, optimism and technology shocks impact nowcast errors in a purely transitory way and, hence, by the same token have a permanent effect on the *cumulative* nowcast error. Other shocks impact neither the nowcast error on impact nor the cumulative nowcast error. While, according to the model, the second result is an immediate implication of the first one, this no longer holds in our VAR, as it features richer dynamics. Hence, we restrict the response of the nowcast error in the short and in the long run.

Lastly, we use a third restriction to tell technology and optimism shocks apart, namely the zero restriction in the second row of the long-run matrix A_0. In this way we rule out a long-run response of labor productivity to optimism shocks. Hence, we use a somewhat weaker assumption here than the commonly employed restriction that, in the long run, labor productivity is driven by technology shocks only (see Galí, 1999, and many others). We merely restrict the long-run impact of optimism shocks on labor productivity to be zero. To the extent that some optimism shocks also impact labor productivity in the long run, our results represent a lower bound for the effects of optimism shocks.

[22] As a matter of fact, our results in Section 4.2 below lend additional credibility to our identification scheme. If there were, additional to technology shocks, other structural shocks that are systematically misperceived by professional forecasters, they are bound to move output by more than expected. Optimism shocks, on the other hand, may have an impact on output, but *less* than expected. This pattern characterizes our results below and reflects the specific nature of optimism shocks: economic activity expands precisely because agents are too optimistic and, hence, overestimate growth (Proposition 2 shows this prediction in the context of our model).

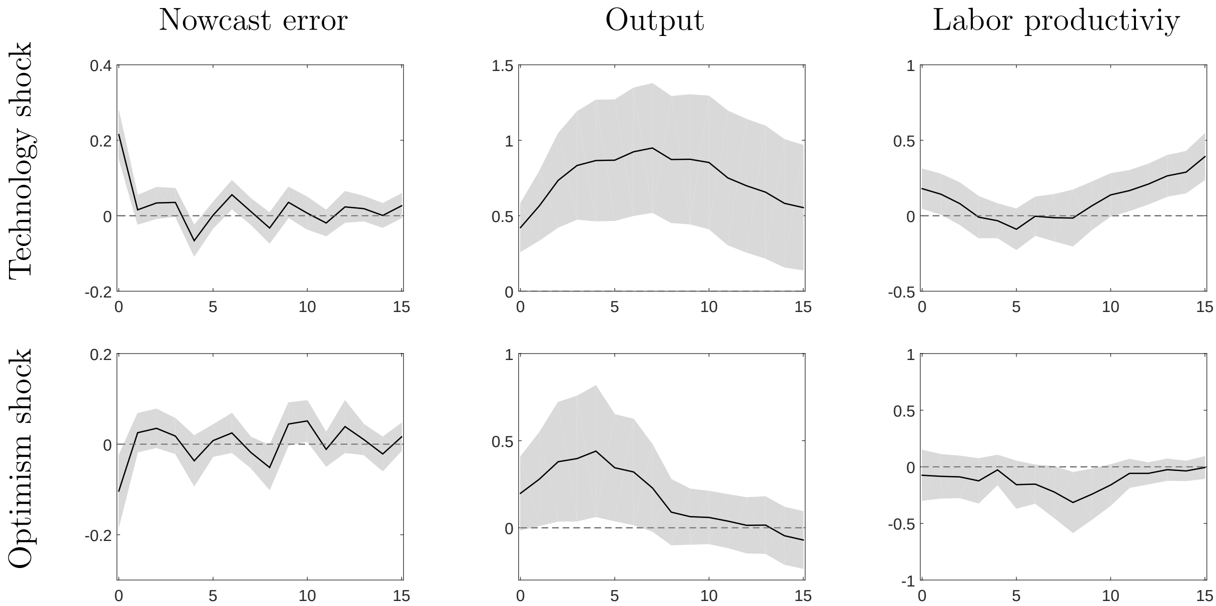

Figure 3: Impulse responses to one-standard-deviation shock under baseline identification. Notes: Solid lines indicate point estimates; shaded areas 90%-confidence bounds obtained by bootstrap sampling (1000 repetitions). Horizontal axes measure quarters. Vertical axes: percentage points in case of nowcast error; percentage deviations from pre-shock level otherwise.

4.2 Results

We compute impulse response functions on the basis of the estimated VAR model and display results in Figures 3-5. In each figure, the top panels display the responses to a technology shock, while the bottom panels show the responses to an optimism shock. In each instance, the size of the shock corresponds to one standard deviation. Solid lines represent the point estimate, while shaded ares indicate 90%-confidence bounds obtained by bootstrap sampling. The columns in Figure 3 display the responses of the nowcast error, output (implied by those of labor productivity and hours), and labor productivity. Here and in the figures below, horizontal axes measure time in quarters, while vertical axes measure deviations from the pre-shock level in percent (or in percentage points in the case of the nowcast error).

A first important result is the joint response of the nowcast error and output to both structural shocks. While technology shocks induce a positive comovement of output and the nowcast error, optimism shocks induce a negative comovement. Recall that the comovement is unrestricted under our identification scheme. Yet, in line with the prediction of the model developed in Section 3, we find that optimism shocks induce a negative nowcast

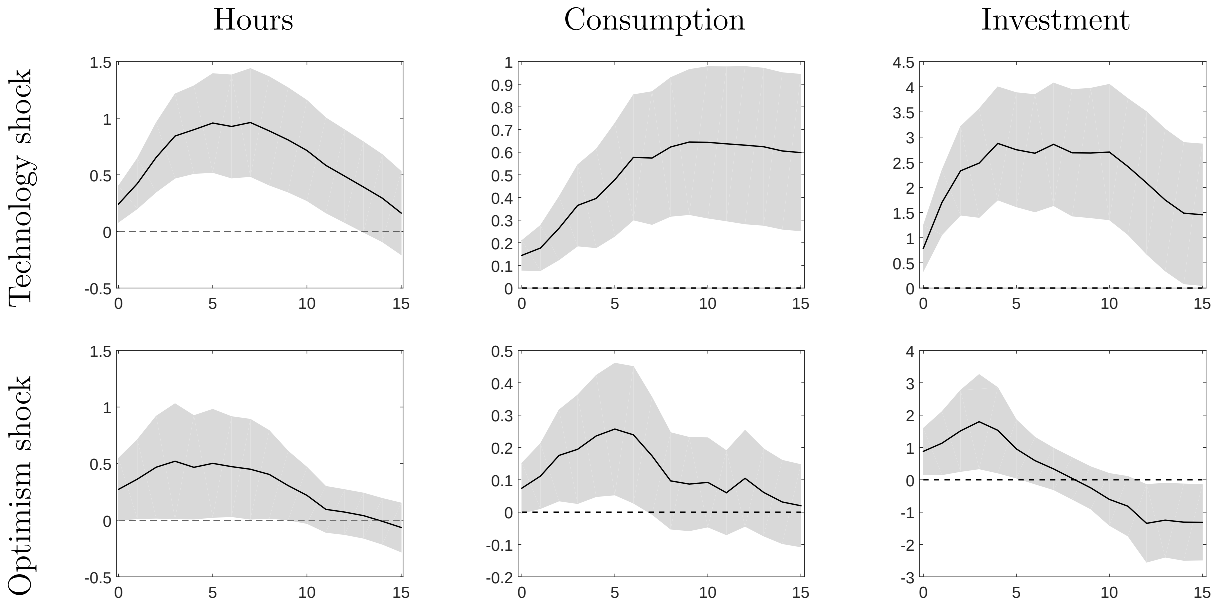

Figure 4: Impulse responses to one-standard-deviation shock under baseline identification. Notes: Solid lines indicate point estimates, shaded areas 90%-confidence bounds obtained by bootstrap sampling (1000 repetitions). Horizontal axes measure quarters. Vertical axes: percentage points in case of nowcast error, percentage deviations from pre-shock level otherwise.

error and boost the level of economic activity at the same time. This finding is particularly remarkable in light of the unconditional positive comovement of nowcast errors and output (see Section 2). In our view, it lends additional support to our identification strategy.

The response of the nowcast error is short-lived, while the response of output to both shocks is sizeable, hump-shaped and persistent. Comparing the response to technology shocks and optimism shocks, we find that optimism shocks induce a weaker and shorter-lived response. The response of output to optimism shocks, in particular, ceases to be significant after less than two years, while the response to technology shocks is still significant after four years. The third column shows the response of labor productivity. It increases in response to a technology shock on impact, and particularly in the long run. Instead, labor productivity remains basically flat after an optimism shock.

We display the responses of hours in the first column of Figure 4. They show a sharper, hump-shaped pattern in response to the technology shock, but also increase in response to the optimism shock. In the long run, they are back to the pre-shock level in both instances. In order to flesh out the transmission mechanism of optimism shocks, we consider further variables and include them in VAR model. To economize on the degrees of freedom, we add

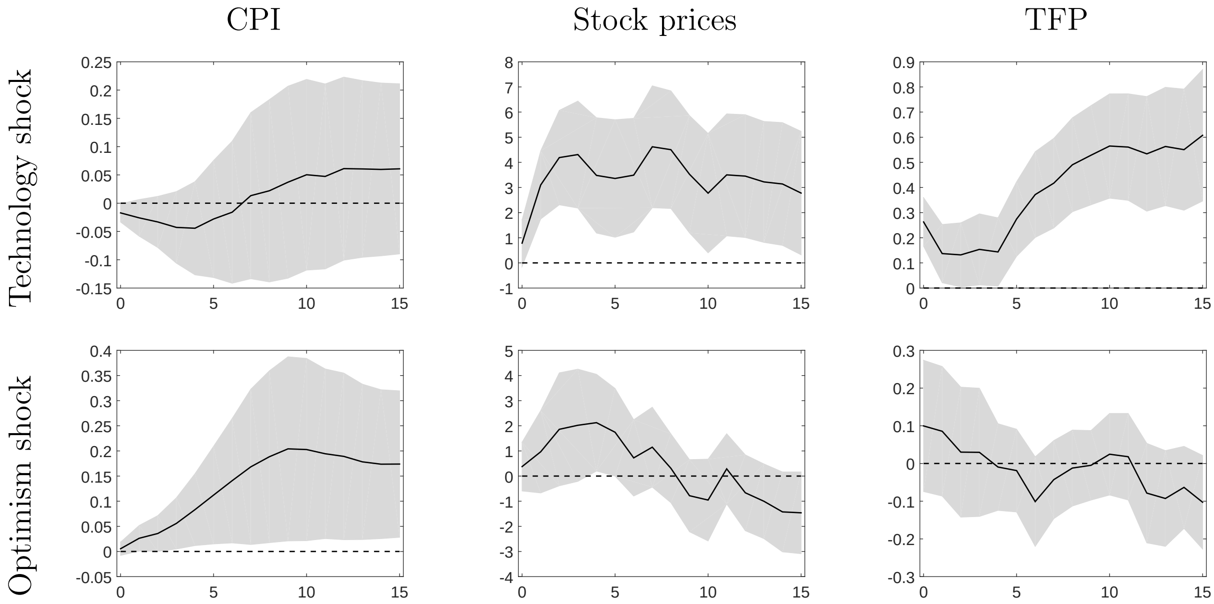

Figure 5: Impulse responses to one-standard-deviation shock under baseline identification. Notes: Solid lines indicate point estimates, shaded areas 90%-confidence bounds obtained by bootstrap sampling (1000 repetitions). Horizontal axes measure quarters. Vertical axes: percentage points in case of nowcast error, percentage deviations from pre-shock level otherwise.

variables sequentially and reestimate the resulting four-variable VAR in each instance.[23] Results for consumption and investment are shown in Figure 4.[24] We find that technology and optimism shocks raise consumption and investment, although the effect is again stronger and more persistent in the case of technology shocks.

The first column of Figure 5 shows the response of the consumer price index.[25] We find that technology shocks are weakly deflationary in the short run. Optimism shocks, instead, induce a significant rise in the price level. They thus share important features of what has been traditionally referred to as a "demand shock". The second column of Figure 5 shows the response of stock prices in real terms.[26] They increase strongly in response to technology shocks, but also rise in response to optimism shocks. Finally, in the last column, we show the response of a direct measure of total factor productivity

[23]We add the fourth variable in first differences of the natural logarithm. We rule out that the fourth element in ε_t impacts contemporaneously any other variable but the one added to the VAR. We do not attach a structural interpretation to the fourth shock.

[24]Consumption is measured by real personal consumption expenditures and investment by real gross private domestic investment, both obtained from the BEA.

[25]The consumer price index refers to all urban consumers and all items less energy (BLS).

[26]We consider quarterly averages of the S&P 500 Composite, deflated by the CPI index and divided by the civilian non-institutional population provided by Datastream and the BLS, respectively.

Table 3: Forecast error variance decomposition

	Horizon	Technology	Optimism	Unlab
Nowcast error	1	81.18	18.82	0.00
	4	78.73	20.78	0.49
	12	67.26	25.73	7.01
	20	65.25	26.64	8.11
Output	1	52.63	11.60	35.77
	4	60.09	14.54	25.36
	12	69.35	8.030	22.62
	20	71.08	6.927	21.99
Labor productivity	1	17.09	2.960	79.95
	4	11.72	7.130	81.15
	12	11.48	30.78	57.74
	20	53.75	12.45	33.81
Hours	1	43.53	55.23	1.24
	4	63.44	32.17	4.39
	12	71.53	19.04	9.43
	20	70.68	19.11	10.21

Notes: VAR model under baseline identification; each panel reports the decomposition of the forecast error variance for the variable of interest (in %), considering a forecast horizon of 1, 4, 12 and 20 quarters. Each of the three right-most columns reports the contribution of one shock type.

(adjusted for the utilization of capital and labor). It displays a strong and lasting increase after a technology shock but no significant reaction to optimism shocks in either the short or the long run.

Overall, we consider the dynamics triggered by optimism shocks as plausible. Hence, we turn to the question of to what extent optimism shocks are an autonomous source of business cycle fluctuations. In order to gauge their contribution to economic fluctuations, we compute a forecast error variance decomposition. Table 3 reports the results for the variables of our baseline VAR model. Regarding the nowcast error (first panel), we find that it is driven mostly by technology shocks. Still, optimism shocks account for about one quarter of the forecast error variance. Technology shocks account for the bulk of fluctuations in output (second panel), yet optimism shocks also contribute substantially. In the short run, their contribution amounts to about 15 percent. Technology shocks also dominate optimism shocks as a driving force for variations in labor productivity in the short run (third panel), while the opposite holds for hours (fourth panel).

Our findings are similar in magnitude to what Blanchard et al. (2013) find. They estimate a medium-scale DSGE model featuring "noise shocks". These shocks are structurally identical to optimism shocks as defined in the present paper and found to account for about 20 percent of short-run output volatility.[27] Instead, Barsky and Sims (2012), estimating a fully specified DSGE model by means of indirect inference methods, find that "animal spirit" shocks account for almost none of the volatility of output. While their animal spirit shock is conceptually closely related to optimism shocks, it is restricted to pertain to future productivity (growth) only. Moreover, their analysis is centered around innovations in consumer confidence as reported by the Michigan Survey of Consumers. They find these innovations to reflect correctly anticipated future output growth, that is, according to their estimates, confidence innovations represent news rather than undue optimism. Reassuringly, once we include their time series of confidence innovations as an additional variable in our VAR model, we find it to be driven mostly by innovations that are orthogonal to optimism shocks.[28]

In a last step, we use the estimated VAR model to measure the contribution of optimism and technology shocks to actual output fluctuations. Figure 6 represents a historical decomposition of U.S. output fluctuations. The panels show the contribution of technology shocks (top) and optimism shocks (bottom) to output growth (beyond the average). Shaded areas indicate NBER recessions. According to our estimates, the role of optimism shocks has been different in each of the three recessions. While the 1990–91 recession took place against the backdrop of weak contributions of technology to output growth, our results are consistent with the notion that pessimism shocks may have triggered the recession (Blanchard, 1993). At the same time, we observe that optimism contributed to the quick output recovery in the following years. Regarding the 2001 recession, there was apparently no contribution of optimism shocks. Recall, however, that the recession was preceded by the bust in U.S. equity markets in 2000—precisely at the time when pessimism was a ma-

[27]In a similar exercise, Hürtgen (2014) obtains a value of 14 percent. While conceptually distinct, it might be noteworthy that the contribution of "noisy news" to the short-run fluctuations of output amounts to some 50 percent, according to Forni et al. (2017).

[28]Specifically, we include the innovations as an additional variable in our baseline VAR. Retaining a just-identified system, we identify a fourth shock that impacts only confidence innovations contemporaneously. Computing a forecast error variance decomposition, we find that about 18 percent of the short-run variance of confidence innovations is due to technology shocks, while another 78 percent is driven by the confidence-specific shock. The optimism shock, however, accounts for less than 2 percent. Moreover, optimism shocks have no significant impact on confidence innovations.

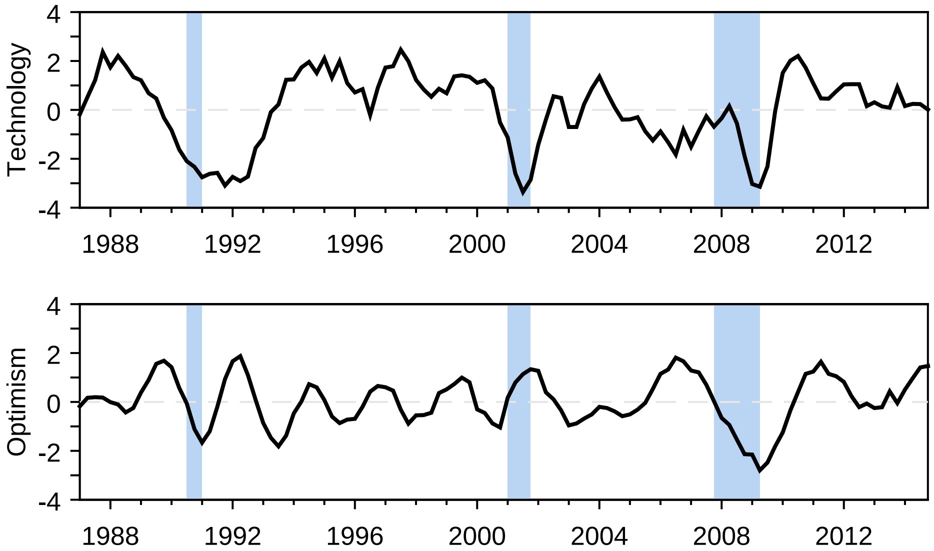

Figure 6: Historical decomposition of output growth. Notes: Contribution of technology and optimism shocks to the quarter-on-quarter growth rate of GDP. Shaded areas indicate NBER recessions.

jor drag on GDP growth. Turning to the Great Recession, we detect a very strong role played by optimism. It contributed strongly to output growth in the run-up to the recession. From around 2007 onwards, the contribution started to decline and turned negative precisely when the recession began. Importantly, the impact of pessimism remained strong after the recession ended. Hence, in contrast to technology shocks, (undue) pessimism played an important role in the sluggishness of the recovery after 2009.

4.3 Partial identification

In what follows, we show that our results are robust to relaxing our identification restrictions. Specifically, we consider four alternative sets of identification restrictions where, in each instance, we no longer impose a unique structural model B. Instead we permit a *set of* models, each consistent with these weaker restrictions, that is, we seek "partial identification" only (for further details, see, for instance, Kilian, 2013). Correspondingly, to account for parameter uncertainty, not only in terms of the structural model B but also in terms of the reduced form, we re-estimate our VAR model using Bayesian techniques. Specifically, we estimate a Bayesian VAR (BVAR) model while entertaining a flat normal-inverse-Wishart prior.

In the first specification, we relax our identification restrictions on the response of the nowcast error and rely merely on a "size restriction". We no longer require the nowcast error to respond only to technology shocks and optimism shocks. Rather, we permit it to respond to other shocks as well—in both the short and the long run. Yet, for the short run, we assume that both technology and optimism shocks impact nowcast errors contemporaneously more strongly than any other shock.[29] The response of the nowcast error in the long run remains unrestricted, while the long-run response of labor productivity to optimism shocks is still required to be zero. We refer to this identification scheme as "alternative identification I".

In the remaining three alternative specifications II-IV, we employ sign restrictions (Uhlig, 2005). Specifically, we make use of the fact that optimism shocks can be characterised by their relative impact on GDP and the nowcast error: a positive optimism shock raises output, but less than expected. That is, on impact GDP increases while the nowcast error falls. Positive technology shocks, on the other hand, are assumed to induce a positive nowcast error and a non-negative GDP response, as they raise economic activity beyond the expected level. This pattern emerges under the baseline identification scheme, thereby lending additional support to its plausibility. Under alternative identifications II-IV, we directly impose **it** and study potential differences in the estimated responses relative to the baseline. As we restrict the output response under the sign restriction scheme directly, we include GDP in the VAR model rather than hours worked.[30]

In addition, under alternative identification II, to separate technology and optimism shocks, we maintain the short-run restriction that nowcast errors are only due to technology or optimism shocks (as in the baseline identification scheme). Next, in analogy to alternative identification I, we relax this short-run restriction by combining the sign restrictions with the size restriction that technology and optimism shocks have a larger impact on the nowcast error than the remaining shock ("alternative identification III"). Finally, we consider a specification which only uses the sign restrictions and hence dispose of further zero or size restrictions. In this version, we can distinguish between two shocks: one that induces a negative co-movement between the nowcast error and GDP (optimism shocks) and all others. We therefore estimate a bivariate VAR model on the nowcast error and

[29]We require their contribution to the forecast error variance at horizon 1 to be larger than those of other shocks. That is, the coefficient that determines the impact of the unlabeled shock on the nowcast error in the matrix B is imposed to be smaller in absolute value than the corresponding entries for the technology and optimism shocks.

[30]In this case we estimate the VAR in levels to account for a possible cointegration relationship between labor productivity and (per capita) output.

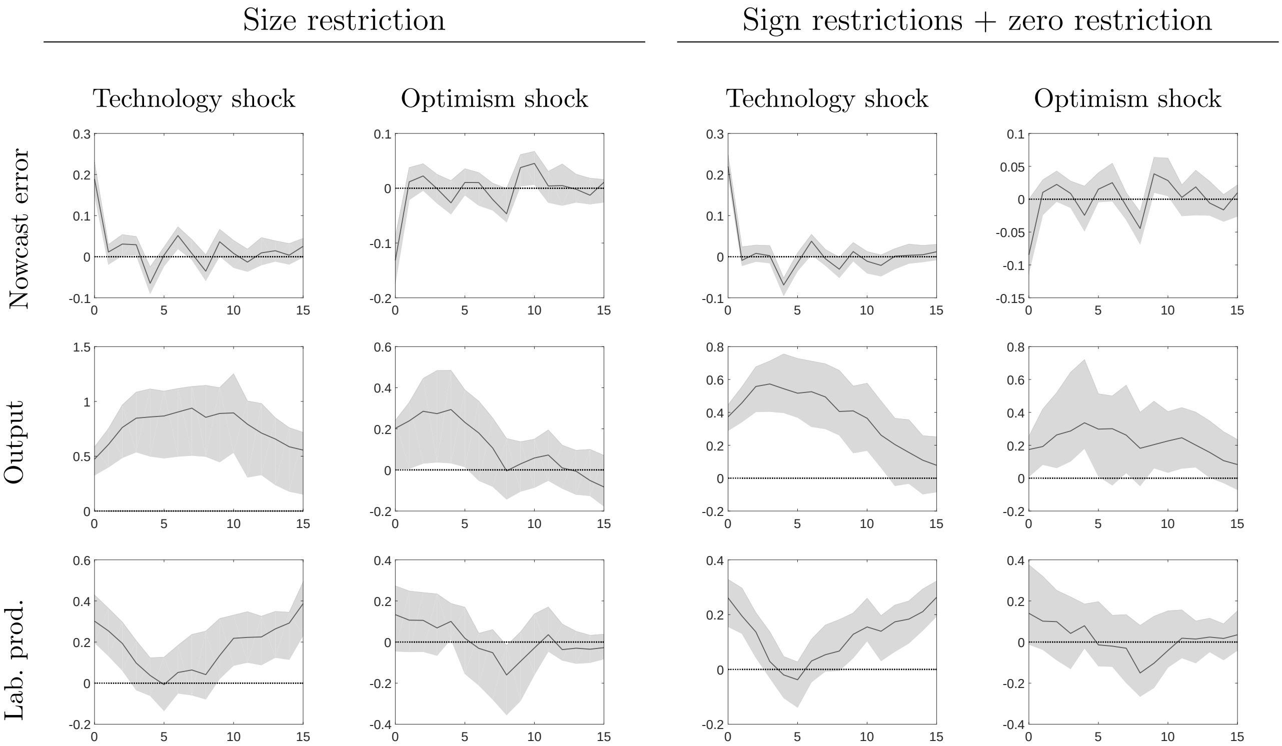

Figure 7: Impulse responses to technology and optimism shock under partial identification. Notes: Left panel shows results for size restriction on nowcast error (alternative identification I); right panel shows results for identification based on sign restrictions with short-run zero restriction on nowcast error (alternative identification II). Solid lines display the median response; shaded areas indicate 68% highest-posterior-density intervals. Horizontal axes measure quarters. Vertical axes: percentage points in case of nowcast error; percentage deviations from pre-shock level otherwise.

GDP. To implement combinations of sign and zero restrictions (alternative identification II-IV), we use the algorithm of Arias et al. (2018).[31] In terms of the sample period, the lag length, and trends, we stick to the baseline specification throughout.

We compute impulse responses for all four identification schemes and report results in Figures 7 and 8. In each case, the solid line corresponds to the median response, while the shaded area represents the 68% highest-posterior-density interval. The left panel of

[31]For alternative specification I, we draw from the unrestricted posterior distribution of the BVAR parameters. For each draw, we systematically rotate the impact matrix on a grid with 5,000 gridpoints, which spans the entire admissible space that satisfies the long-run zero restriction, and keep those rotations that satisfy the size restriction. We repeat the whole procedure until we have 100,000 responses that fulfill the identification restrictions. As Baumeister and Hamilton (2015) point out, it is generally impossible to place flat priors on all coefficients of the impact matrix. Since we lack evidence to generate reasonable prior distributions for most of the elements in B, we simply opt for uniform distributions of the angles of our rotation matrix.

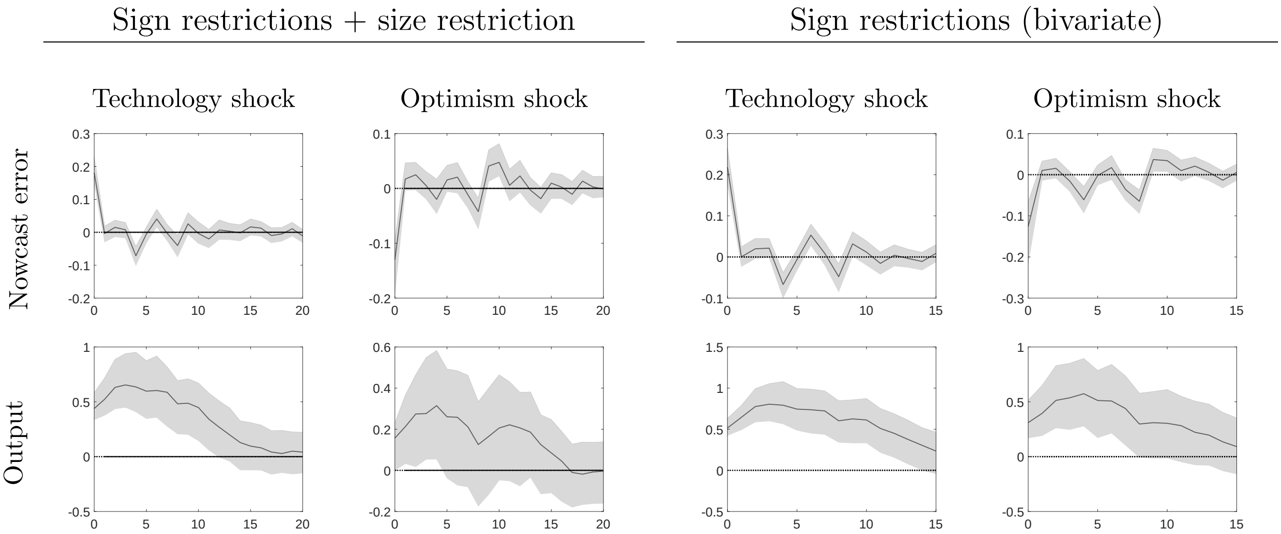

Figure 8: Impulse responses to technology and optimism shock under partial identification. Notes: identifications based on sign restrictions. Left panel shows results for specification with size restriction on nowcast error (alternative identification III); right panel shows results for bivariate VAR (alternative identification IV). Solid lines display the median response; shaded areas indicate 68% highest-posterior-density intervals. Horizontal axes measure quarters. Vertical axes: percentage points in case of nowcast error; percentage deviations from pre-shock level otherwise.

Figure 7 shows results once we impose the size restriction on the nowcast error (alternative identification I). The right panel shows the results for alternative identificatuon II (sign-restrictions plus the short-run zero restriction on the nowcast error). Figure 8 displays the impulse-responses for alternative identification III, sign restrictions plus a size restriction on the nowcast error, in the left panel. In this case we omit the responses of labor productivity, because they are very similar to those shown in Figure 7. The right panel shows the results of the bivariate VAR (alternative specification IV). In all panels, the left column shows the impulse responses to a technology shock while the right column features the impulse responses to an optimism shock.

Overall, results are very similar to those obtained for the baseline identification scheme—not only qualitatively but also quantitatively (see Figure 3). In sum, we find that our results are robust once we consider weaker or alternative identification assumptions. In particular, optimism shocks have a short-lived expansionary effect on GDP, while the response of labor productivity (unrestricted under all alternative identification schemes) is insignificant.

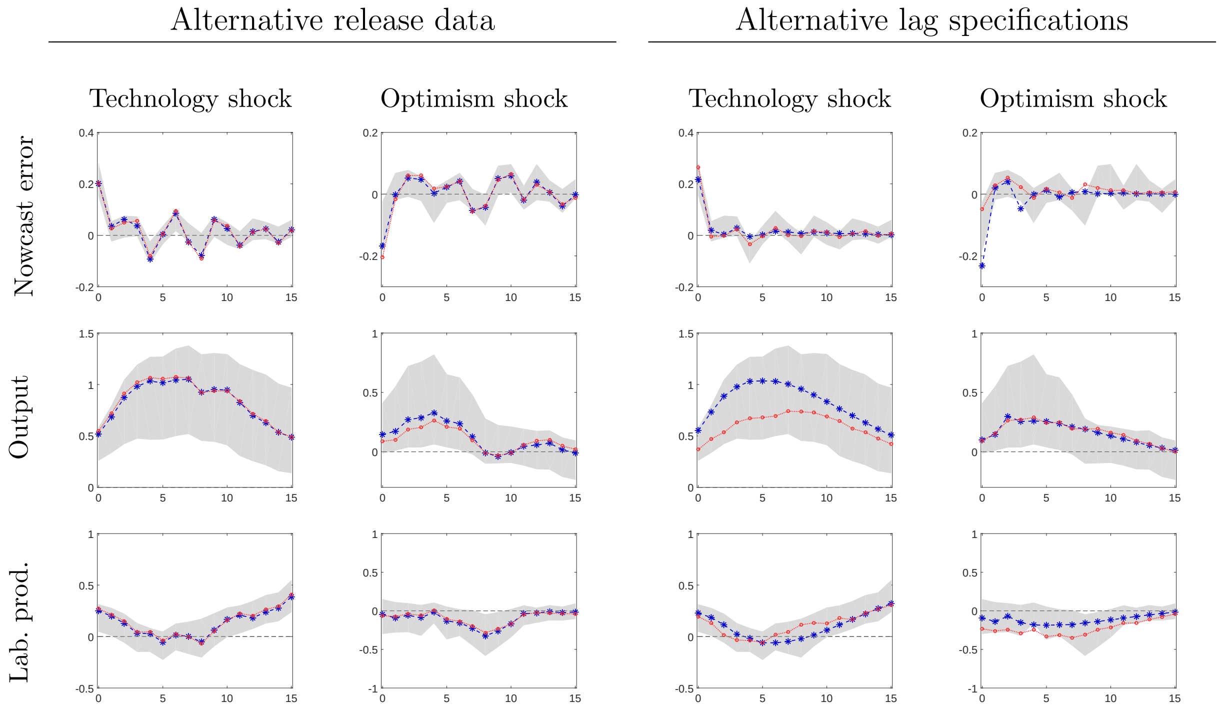

Figure 9: Impulse responses to technology and optimism shock under alternative model specifications (baseline identification). Notes: Shaded areas indicate bootstrapped 90%-confidence intervals of baseline specification (see Figure 3). Left: lines with $*$ ($\circ$): point estimate for model with nowcast error based on second-release (final) data rather than first-release data. Right panel $*$ ($\circ$): point estimate for model estimated on 4 (8) lags rather than 12 lags. Horizontal axes measure quarters. Vertical axes: percentage points in case of nowcast error; percentage deviations from pre-shock level otherwise.

4.4 Further sensitivity analysis

We also conduct a number of experiments to explore the robustness of the results while maintaining our baseline identification scheme. First, we consider alternative measures of the nowcast error, as it is central to our identification strategy. Our baseline VAR model is estimated on nowcast errors computed on the basis of first-release data for current GDP growth. Results in Section 2 suggest that nowcast errors differ somewhat depending on the release by the BEA. Hence, we reestimate the baseline VAR model on time-series for the nowcast error based, in turn, on the second and final release of the BEA. The left panel of Figure 9 shows the results. The shaded area represents the confidence interval of the baseline specification (first-release data), while the solid lines with markers represent the alternative specifications. In both instances, we observe only minor differences relative to the baseline specification.

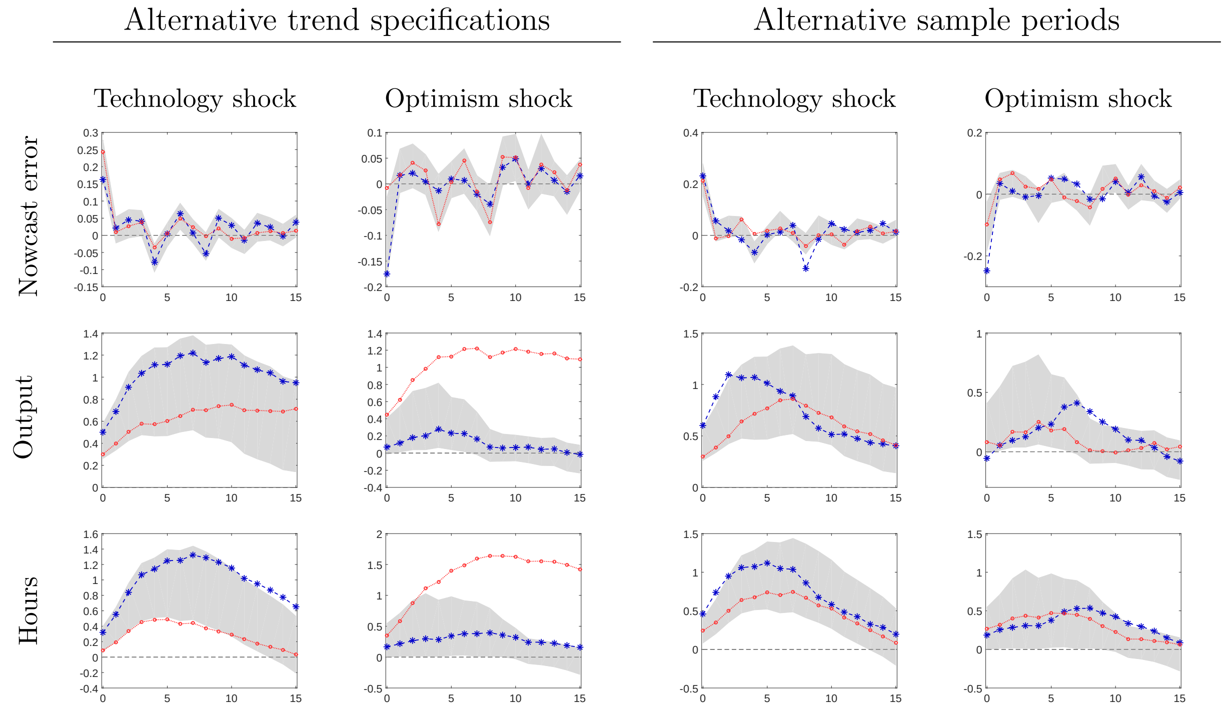

Figure 10: Impulse responses to technology and optimism shock under alternative model specifications (baseline identification). Notes: Shaded areas indicate bootstrapped 90%-confidence intervals of baseline specification (see Figure 3). Left: lines with $*$ ($\circ$): point estimate for model with hours linearly detrended (in first differences) rather than with linear quadratic trend. Right panel $*$ ($\circ$): point estimate for model estimated on data for 1968Q4–2014Q4 (1983Q1–2007Q4) rather than 1983Q1–2014Q4. Horizontal axes measure quarters. Vertical axes: percentage points in case of nowcast error; percentage deviations from pre-shock level otherwise.

Next, we show results for specifications where we vary the number of lags included in the VAR model in the right panel of Figure 9. The shaded area represents again the confidence interval of the baseline specification (12 lags). Lines with markers represent the point estimates obtained for 4 and 8 lags, respectively. It turns out that results are similar across specifications. The point estimates for the alternative specifications are included in the confidence interval of the baseline in all instances.

We also investigate robustness with respect to alternative assumptions regarding the trend in the time series for hours worked. This issue has received considerable attention in the literature, as some studies found the trend specification to be crucial for the sign of the response of hours worked to a technology shock. This is not the case in our setup, as the left panel of Figure 10 illustrates. Here, as before, the shaded area corresponds to the baseline specification (linear-quadratic trend), while lines with circles represent the point

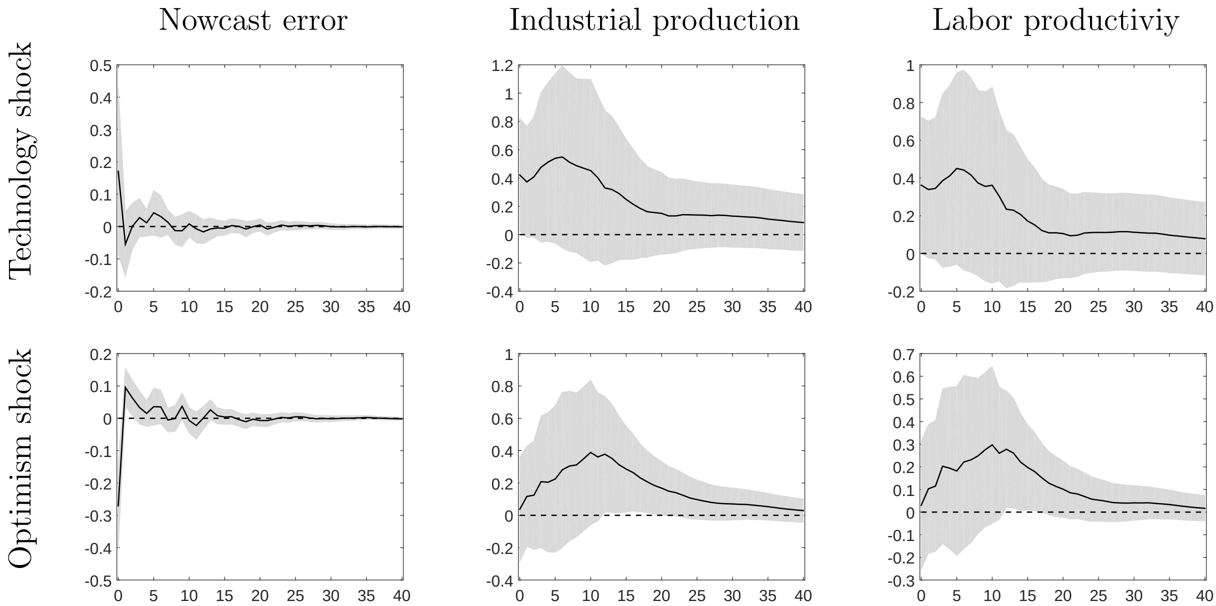

Figure 11: Impulse responses to technology and optimism shock, given monthly observations (baseline identification). Notes: Sample is 1996M10–2014M12; nowcast error based on Bloomberg's survey of professional forecasters for industrial production. Horizontal axes measure months. Vertical axes: percentage points in case of nowcast error; percentage deviations from pre-shock level otherwise.

estimate for a specification where hours enter in first differences and lines with asterisks correspond to a specification with a linear time trend. We find once more that results are not strongly affected by these modifications to the VAR setup, not only in the case of the response of hours but also those of output and labor productivity.[32] We also find that results are not sensitive to whether hours worked and labor productivity correspond to the entire business sector (baseline) or to the non-farm business sector (not shown).

The right panel of Figure 10, in turn, contrasts results for different sample periods. The shaded area represents the confidence interval for the baseline sample (1983Q1–2014Q4). Lines with an asterisk represent results when the baseline VAR model is estimated on the longest possible sample for which data are available (1968Q4–2014Q4); lines with circles correspond to a sample where we drop observations for the financial crisis. Again, results are fairly similar to those obtained for the baseline sample.

Finally, we explore to what extent results are robust once we consider a different sampling frequency, because our identification strategy relies on assumptions regarding the available information at the time forecasters are asked to predict current output growth.

[32]Not shown. In the difference specification, there is a permanent effect of optimism shocks on output and hours. The long-run effects, however, are not significant.

Specifically, forecasters are assumed to have no information regarding current innovations in output growth. Due to the frequency of releases of GDP data, our baseline VAR model is estimated on quarterly observations. In order to construct an alternative monthly measure of the nowcast error, we use data for industrial production and a survey of professional forecasters by Bloomberg.[33] Results are shown in Figure 11. They are in line with those obtained for the baseline VAR model, despite considerable differences in the sample (1996M10–2014M12), data frequency, and the measure of economic activity.

5 Conclusion

Are business cycle fluctuations caused by undue optimism and, if so, to what extent? In this paper, we pursue a new approach to address this question. Barsky and Sims (2012) and Blanchard et al. (2013) estimate fully specified DSGE models to quantify the importance of "noise" or "undue optimism". This approach is fairly restrictive as it imposes a lot of specific restrictions on the data. Moreover, both studies reach quite different conclusions as to the quantitative importance of optimism shocks. We therefore pursue an alternative, less restrictive approach based on a structural VAR model. Yet, as shown by Blanchard et al. (2013), identifying the effects of optimism shocks within VAR models constitutes a formidable challenge.

Our empirical strategy is based on an *ex post* informational advantage over market participants. Namely, we compute nowcast errors regarding current output growth as the difference between actual output growth and the median nowcast of the Survey of Professional Forecasters. Nowcast errors are a reduced-form measure of misperceptions, which we show to respond systematically to innovations in total factor productivity. However, we do not find them to be significantly affected by policy innovations or uncertainty shocks, which are, to some degree, contemporaneously observable by market participants.

Drawing on Lorenzoni (2009), we put forward a stylized business cycle model that gives rise to nowcast errors due to technology and optimism shocks, as agents do not observe output contemporaneously. Shocks that are common information do not generate a nowcast error. Importantly, we use this model to show that optimism shocks can be identified in a VAR model that includes time-series data on nowcast errors.

[33] The Bloomberg survey forecasts have been available since 1996M10. We consider data up to 2014M12. Since there is no time series for hours that corresponds directly to industrial production, we use the natural logarithm of average weekly hours in manufacturing as reported by the BLS. We compute the growth rate of labor productivity as the difference between the growth rates of the volume index of industrial production in the manufacturing sector (source: Federal Reserve) and average weekly hours in manufacturing. We estimate the VAR on 12 lags and a linear time trend.

We estimate our VAR model on U.S. time series for the period 1983Q1–2014Q4 and identify unanticipated shocks to technology and optimism shocks by combining short and long-run restrictions. Specifically, we assume for our baseline identification scheme that only optimism shocks and technology shocks generate nowcast errors and that only technology shocks impact labor productivity permanently. We find that, while both shocks raise output persistently, their effect on the nowcast error differs. Technology shocks induce a positive nowcast error, that is, growth turns out to be higher than expected. Optimism shocks, on the other hand, induce a negative nowcast error, that is, growth turns out to be lower than expected. After all, professional forecasters have been too optimistic in this case.

According to the forecast error variance decomposition, the contribution of optimism shocks to output fluctuations amounts to about 15 percent. This is a sizeable contribution. Still, the fact that the unconditional correlation between the nowcast error and output growth is positive also suggests that optimism shocks are not the major source of business cycle fluctuations. By their very nature, optimism shocks induce a negative comovement of nowcast errors and output growth. The fact that we uncover such a negative comovement in our VAR framework conditional on optimism shocks lends plausibility to our approach and makes us confident that we are indeed able to identify optimism shocks in actual time-series data.

References

Angeletos, G.-M., Collard, F., and Dellas, H. (2017). Quantifying confidence. *Econometrica*, forthcoming.

Angeletos, G.-M. and La'O, J. (2013). Sentiments. *Econometrica*, 81:739–779.

Arias, J. E., Rubio-Ramírez, J. F., and Waggoner, D. F. (2018). Inference based on SVARs identified with sign and zero restrictions: Theory and applications. *Econometrica*, 86:685–720.

Bachmann, R. and Sims, E. R. (2012). Confidence and the transmission of government spending shocks. *Journal of Monetary Economics*, 59:235–249.

Barsky, R. B. and Sims, E. R. (2011). News shocks and business cycles. *Journal of Monetary Economics*, 58:273–289.

Barsky, R. B. and Sims, E. R. (2012). Information, animal spirits, and the meaning of innovations in consumer confidence. *American Economic Review*, 52:1343–1377.

Baumeister, C. and Hamilton, J. D. (2015). Sign restrictions, structural vector autoregressions, and useful prior information. *Econometrica*, 83(5):1963–1999.

Beaudry, P., Nam, D., and Wang, J. (2011). Do mood swings drive business cycles and is it rational? NBER Working Paper 17651.

Beaudry, P. and Portier, F. (2004). An exploration into Pigou's theory of cycles. *Journal of Monetary Economics*, 51:1183–1216.

Beaudry, P. and Portier, F. (2006). Stock prices, news, and economic fluctuations. *American Economic Review*, 96:1293–1307.

Blanchard, O. (1993). Consumption and the recession of 1990–91. *American Economic Review*, 83:270–274.

Blanchard, O., L'Huillier, J.-P., and Lorenzoni, G. (2013). News, noise, and fluctuations: An empirical investigation. *American Economic Review*, 103:3045–70.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3):623–685.

Carroll, C. D., Fuhrer, J. C., and Wilcox, D. W. (1994). Does consumer sentiment forecast household spending? If so, why? *American Economic Review*, 84(5):1397–1408.

Chari, V., Kehoe, P. J., and McGrattan, E. R. (2008). Are structural VARs with long-run restrictions useful in developing business cycle theory? *Journal of Monetary Economics*, 55:1337–1352.

Clarida, R., Galí, J., and Gertler, M. (2000). Monetary policy rules and macroeconomic stability: Evidence and some theory. *Quarterly Journal of Economics*, 115:147–180.

Coibion, O. (2012). Are the Effects of Monetary Policy Shocks Big or Small? *American Economic Journal: Macroeconomics*, 4(2):1–32.

Coibion, O. and Gorodnichenko, Y. (2012). What can survey forecasts tell us about information rigidities? *Journal of Political Economy*, 120(1):116–159.

Coibion, O. and Gorodnichenko, Y. (2015). Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts. *American Economic Review*, 105(8):2644–78.

Coibion, O., Gorodnichenko, Y., Kueng, L., and Silvia, J. (2017). Innocent Bystanders? Monetary policy and inequality. *Journal of Monetary Economics*, 88(C):70–89.

Croushore, D. (1993). Introducing: the survey of professional forecasters. *Business Review*, 6.

De Graeve, F. and Westermark, A. (2013). Un-truncating VARs. Riksbank Research Paper Series No. 102.

Fernald, J. (2014). A quarterly, utilization-adjusted series on total factor productivity. Federal Reserve Bank of San Francisco Working Paper 2012-19.

Fernández-Villaverde, J., Rubio-Ramírez, J. F., Sargent, T., and Watson, M. W. (2007). ABCs (and Ds) of understanding VARs. *American Economic Review*, 97(3):1021–1026.

Fisher, J. D. M. (2002). Technology shocks matter. Working Paper Series WP-02-14, Federal Reserve Bank of Chicago.

Fisher, J. D. M. (2006). The Dynamic Effects of Neutral and Investment-Specific Technology Shocks. *Journal of Political Economy*, 114(3):413–451.

Forni, M., Gambetti, L., Lippi, M., and Sala, L. (2017). Noisy news in business cycles. *American Economic Journal: Macroeconomics*, 9(4):122–52.

Francis, N. and Ramey, V. A. (2005). Is the technology-driven real business cycle hypothesis dead? Shocks and aggregate fluctuations revisited. *Journal of Monetary Economics*, 52(8):1379–1399.

Galí, J. (1999). Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? *American Economic Review*, 89:249–271.

Galí, J. and Rabanal, P. (2005). Technology shocks and aggregate fluctuations: How well does the real business cycle model fit postwar U.S. data? In *NBER Macroeconomics Annual 2004*, volume 19, pages 225–318. National Bureau of Economic Research, Inc.

Gennaioli, N., Ma, Y., and Shleifer, A. (2015). Expectations and Investment. In *NBER Macroeconomics Annual 2015, Volume 30*, NBER Chapters, pages 379–431. National Bureau of Economic Research, Inc.

Giannone, D., Reichlin, L., and Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, 55(4):665–676.

Hürtgen, P. (2014). Consumer misperceptions, uncertain fundamentals, and the business cycle. *Journal of Economic Dynamics and Control*, 40:279–292.

Jaimovic, N. and Rebelo, S. (2009). Can news about the future drive the business cycle? *American Economic Review*, 96:1097–1118.

Johansen, S. (1995). *Likelihood-based inference in cointegrated vector autoregressive models.* Oxford University Press.

Jordà, O. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95:161–182.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3):1177–1216.

Keynes, J. M. (1936). *The General Theory of Employment, Interest, and Money.* Edition Harvest/Harcourt Brace 1964, Orlando, Florida.

Kilian, L. (2001). Impulse response analysis in vector autoregressions with unknown lag order. *Journal of Forecasting*, 20(3):161–79.

Kilian, L. (2008). Exogenous Oil Supply Shocks: How Big Are They and How Much Do They Matter for the U.S. Economy? *The Review of Economics and Statistics*, 90(2):216–240.

Kilian, L. (2013). Structural vector autoregressions. In *Handbook of Research Methods and Applications in Empirical Macroeconomics*, chapter 22, pages 515–554. Edward Elgar Publishing.

Leduc, S. and Sill, K. (2013). Expectations and economic fluctuations: An analysis using survey data. *The Review of Economics and Statistics*, 95:1352–1367.

Lorenzoni, G. (2009). A theory of demand shocks. *American Economic Review*, 99:2050–2084.

McConnell, M. M. and Perez-Quiros, G. (2000). Output fluctuations in the United States: What has changed since the early 1980s? *American Economic Review*, 90:1464–1476.

Melosi, L. (2017). Signaling effects of monetary policy. *Review of Economic Studies*, 84:853–884.

Milani, F. (2011). Expectation shocks and learning as drivers of the business cycle. *Economic Journal*, 121:379–401.

Mora, J. V. R. and Schulstad, P. (2007). The effect of GNP announcements on fluctuations of GNP growth. *European Economic Review*, 51:1922–1940.

Nakamura, E. and Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: The information effect. *The Quarterly Journal of Economics*. forthcoming.

Nimark, K. P. (2014). Man-Bites-Dog Business Cycles. *American Economic Review*, 104(8):2320–67.

Nordhaus, W. D. (1987). Forecasting efficiency: Concepts and applications. *The Review of Economics and Statistics*, 69(4):667–674.

Oh, S. and Waldman, M. (1990). The macroeconomic effects of false announcements. *The Quarterly Journal of Economics*, 105:1017–1034.

Pigou, A. C. (1927). *Industrial Fluctuations*. Macmillan.

Ramey, V. (2014). Defense news shocks, 1889-2013: Estimates based on news sources. Mimeo.

Romer, C. D. and Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American Economic Review*, 94(4):1055–1084.

Romer, C. D. and Romer, D. H. (2010). The macroeconomic effects of tax changes: Estimates based on a new measure of fiscal shocks. *American Economic Review*, 100(3):763–801.

Schmitt-Grohé, S. and Uribe, M. (2012). What's news in business cycles? *Econometrica*, 80:2733–2764.

Smets, F. and Wouters, R. (2007). Shocks and frictions in US business cycles: A Bayesian DSGE approach. *American Economic Review*, 97(3):586–606.

Stark, T. and Croushore, D. (2002). Forecasting with a real-time data set for macroeconomists. *Journal of Macroeconomics*, 24(4):507–531.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52:381–419.

Zarnowitz, V. (1985). Rational expectations and macroeconomic forecasts. *Journal of Business & Economic Statistics*, 3(4):293–311.

Appendix

In Appendix B, we provide the proofs for Propositions 1-3 in Section 3. In a preliminary step, we outline the model solution and key equilibrium relationships in Appendix A. Throughout, we consider a linear approximation to the equilibrium conditions of the model. Lower-case letters indicate percentage deviations from steady state.

A Model solution

We solve the model by backward induction. That is, we start by deriving inflation expectations regarding period $t+1$. Using the result in the Euler equation of the third stage of period t allows us to determine price-setting decisions during stage two. Eventually, we obtain the short-run responses of aggregate variables to unexpected changes in productivity or optimism shocks.

Expectations regarding period $t+1$. Below, $E_{k,t}$ stands for either $E_{j,l,t}$, referring to the information set of producer j on island l at the time of her pricing decision, or for $E_{l,t}$, referring to the information set of the household on island l at the time of its consumption decision. Variables with only time subscripts refer to economy-wide values. The wage in period $t+1$ is set according to the expected aggregate labor supply

$$E_{k,t}\varphi l_{t+1} = E_{k,t}(w_{t+1} - p_{t+1} - c_{t+1}).$$

This equation is combined with the aggregated production function

$$E_{k,t}y_{t+1} = E_{k,t}(x_{t+1} + \alpha l_{t+1}),$$

the expected aggregate labor demand

$$E_{k,t}(w_{t+1} - p_{t+1}) = E_{k,t}[x_{t+1} + (1-\alpha)l_{t+1}],$$

and market clearing $y_{t+1} = c_{t+1}$ to obtain $E_{k,t}x_{t+1} = E_{k,t}y_{t+1} = E_{k,t}c_{t+1}$. Furthermore, the expected Euler equation, together with the Taylor rule, is

$$E_{k,t}c_{t+1} = E_{k,t}(c_{t+2} + \pi_{t+2} - \psi\pi_{t+1}).$$

Agents expect the economy to be in a new steady state tomorrow ($E_{k,t}c_{t+1} = E_{k,t}c_{t+2}$), given the absence of state variables other than technology, which follows a unit root process. Ruling out explosive paths yields

$$E_{k,t}\pi_{t+2} = E_{k,t}\pi_{t+1} = 0.$$

Stage three of period *t*. After prices are set, each household observes n prices in the economy. Since the productivity signal is public, the productivity level $a_{j,l,t} = a_{l,t}$—which is the same for all producers $j \in [0,1]$ on island l—can be inferred from each price $p_{j,l,t}$ of the good from producer j on island l. Hence, household l forms its expectations about the change in aggregate productivity according to

$$E_{l,t}\Delta x_t = \rho_x^h s_t + \delta_x^h \hat{a}_{l,t},$$

where $\hat{a}_{l,t}$ is the average over the realizations of $a_{m,t} - x_{t-1}$ for each location m in household l's sample. The coefficients ρ_x^h and δ_x^h are equal across households and depend on $n, \sigma_e^2, \sigma_\varepsilon^2$, and σ_η^2 in the following way:

$$\rho_x^h = \frac{\sigma_\eta^2/n}{\underbrace{\sigma_e^2 + \sigma_\eta^2/n + \frac{\sigma_e^2\sigma_\eta^2/n}{\sigma_\varepsilon^2}}_{\to 0 \text{ if } n\to\infty}}, \qquad \delta_x^h = \frac{\sigma_e^2}{\underbrace{\sigma_e^2 + \sigma_\eta^2/n + \frac{\sigma_e^2\sigma_\eta^2/n}{\sigma_\varepsilon^2}}_{\to 1 \text{ if } n\to\infty}}. \tag{A.1}$$

Producers, on the other hand, only observe the signal and their own productivity. They thus form expectations according to

$$E_{j,l,t}\Delta x_t = \rho_x^p s_t + \delta_x^p (a_{l,t} - x_{t-1}),$$

with

$$\rho_x^p = \frac{\sigma_\eta^2}{\sigma_e^2 + \sigma_\eta^2 + \frac{\sigma_\eta^2 \sigma_e^2}{\sigma_\varepsilon^2}} \qquad \delta_x^p = \frac{\sigma_e^2}{\sigma_e^2 + \sigma_\eta^2 + \frac{\sigma_\eta^2 \sigma_e^2}{\sigma_\varepsilon^2}},$$

such that $\delta_x^h > \delta_x^p$ because of the higher information content of households' observations. Consumption follows an Euler equation with household-specific inflation, as only a subset of goods is bought. Agents expect no differences between households for $t+1$, such that expected aggregate productivity and the overall price level impact today's individual consumption. Also using $E_{l,t}p_{t+1} = E_{l,t}p_t$ and $E_{l,t}x_{t+1} = E_{l,t}x_t$ gives

$$c_{l,t} = E_{l,t}x_t + E_{l,t}p_t - p_{l,t} - r_t. \tag{A.2}$$

Similar to the updating formula for technology estimates, households use their available information to form an estimate about the aggregate price level p_t according to

$$E_{l,t}p_t = \rho_p^h s_t + \delta_p^h \hat{a}_{l,t} + \kappa_p^h w_t + \tau_p^h x_{t-1} - \eta_p^h r_t. \tag{A.3}$$

Combining the above gives

$$c_{l,t} = (1+\tau_p^h)x_{t-1} + \rho_{xp}^h s_t + \delta_{xp}^h \hat{a}_{l,t} + \kappa_p^h w_t - (1+\eta_p^h)r_t - p_{l,t}, \tag{A.4}$$

where $\rho_{xp}^h = \rho_x^h + \rho_p^h$ and $\delta_{xp}^h = \delta_x^h + \delta_p^h$. We will solve for the undetermined coefficients below.

Stage two of period *t*. During the second stage, firms obtain idiosyncratic signals about their productivity. In the following, the index $\tilde{p}_{l,t}$ is the average price index of customers visiting island l. If customers bought on all (that is, infinitely many) islands in the economy, $\tilde{p}_{l,t}$ would correspond to the overall price level. Since consumers only buy on a subset of islands, the price of their own island has a non-zero weight in their price index, which is taken into account further below. Firms set prices according to

$$\begin{aligned} p_{j,l,t} &= w_t + \frac{1-\alpha}{\alpha} E_{j,l,t} y_{j,l,t} - \frac{1}{\alpha} a_{l,t} \\ &\equiv k' + k_1' E_{j,l,t} \tilde{p}_{l,t} + k_2' E_{j,l,t} y_t - k_3' a_{l,t}, \end{aligned}$$

with

$$k' = \frac{\alpha}{\alpha + \gamma(1-\alpha)} w_t \qquad k_1' = \frac{\gamma(1-\alpha)}{\alpha + \gamma(1-\alpha)} \qquad k_2' = \frac{1-\alpha}{\alpha + \gamma(1-\alpha)} \qquad k_3' = \frac{1}{\alpha + \gamma(1-\alpha)}. \tag{A.5}$$

From here onwards, expressions that are based on common knowledge only (such as k') are treated like parameters in notation terms, i.e. they lack a time index. This facilitates the important distinction between expressions that are common information and those that are not. Evaluating the expectation of firm j about aggregate output in period t, given equation (A.4), results in

$$E_{j,l,t} y_t = \kappa^h + \rho_{xp}^h s_t + \delta_{xp}^h E_{j,l,t} \left(\frac{1}{n} a_{l,t} + \frac{n-1}{n} E_{j,l,t} x_t - x_{t-1} \right) - \left(\frac{1}{n} p_{j,l,t} + \frac{n-1}{n} E_{j,l,t} p_t \right),$$

where $\kappa^h = (1+\tau_p^h) x_{t-1} - (1+\eta_p^h) r_t + \kappa_p^h w_t$ contains only publicly available information. Furthermore, it is taken into account that the productivity of island l has a non-zero weight in the sample of productivity levels observed by consumers visiting island l. Note that producers still take the price index of the consumers as given, since they buy infinitely many goods on the same island. Inserting the above into the pricing equation (A.5) yield (here, p_t is the average of the prices charged by producers of all other islands, which is the overall price index as there are infinitely many locations)

$$p_{j,l,t} \equiv k + k_1 E_{j,l,t} p_t + \tilde{k} s_t - k_3 a_{l,t},$$

with

$$\Xi = 1 - \frac{1}{n}(k_1' - k_2') \qquad k = \frac{1}{\Xi} \left\{ k' + k_2' \kappa^h + \frac{k_2' \delta_{xp}^h}{n} \left[(n-1)(1-\delta_x^p) - 1 \right] x_{t-1} \right\} \tag{A.6}$$

$$k_1 = \frac{n-1}{n\Xi} (k_1' - k_2') \qquad \tilde{k} = \frac{k_2'}{\Xi} \left(\rho_{xp}^h + \delta_{xp}^h \rho_x^p \frac{n-1}{n} \right) \qquad k_3 = \frac{1}{\Xi} \left\{ k_3' + \frac{k_2' \delta_{xp}^h}{n} \left[(n-1)\delta_x^p - 1 \right] \right\}.$$

Note that, according to (A.5), $0 < k_1' - k_2' < 1$ because $0 < \alpha < 1$ and $\gamma > 1$. Using the definition of k_1 in (A.6), this implies (observe that $n > 1$)

$$0 < k_1 < 1.$$

Aggregating over all producers gives the aggregate price index

$$p_t = k + k_1 \overline{E}_t p_t + \tilde{k} s_t - k_3 x_t,$$

where $\int a_{l,t} dl = x_t$, and $\overline{E}_t p_t = \iint E_{j,l,t} p_t \, dj dl$ is the average expectation of the price level.

The expectation of firm j of this aggregate is therefore

$$\begin{aligned} E_{j,l,t} p_t &= k + \tilde{k} s_t - k_3 E_{j,l,t} x_t + k_1 E_{j,l,t} \overline{E}_t p_t \\ &= k + \left(\tilde{k} - k_3 \rho_x^p\right) s_t - k_3 \delta_x^p a_{l,t} - k_3 (1 - \delta_x^p) x_{t-1} + k_1 E_{j,l,t} \overline{E}_t p_t. \end{aligned} \tag{A.7}$$

Inserting the last equation into (A.6) gives

$$p_{j,l,t} = k + k_1 k - k_1 k_3 (1 - \delta_x^p) x_{t-1} + \left[\tilde{k} + k_1 \left(\tilde{k} - k_3 \delta_x^p\right)\right] s_t - \left(k_3 + k_1 k_3 \delta_x^p\right) a_t^j + k_1^2 E_{j,l,t} \overline{E}_t p_t.$$

To find $E_{j,l,t} \overline{E}_t p_t$, note that firm j's expectations of the average of (A.7) are

$$E_{j,l,t} \overline{E}_t p_t = k - k_3 (1 - \delta_x^p)(1 + \delta_x^p) x_{t-1} + \left(\tilde{k} - k_3 \rho_x^p - k_3 \delta_x^p \rho_x^p\right) s_t - k_3 \delta_x^{p2} a_{l,t} + k_1 E_{j,l,t} \overline{E}_t^{(2)} p_t,$$

where $\overline{E}^{(2)}$ is the average expectation of the average expectation. The price of firm j is found by plugging the last equation into the second-to-last:

$$\begin{aligned} p_{j,l,t} = &\left(k + k_1 k + k_1^2 k\right) - \left[k_1 k_3 (1 - \delta_x^p) + k_1^2 k_3 (1 - \delta_x^p)(1 + \delta_x^p)\right] x_{t-1} \\ &+ \left[\tilde{k} + k_1 \left(\tilde{k} - k_3 \rho_x^p\right) + k_1^2 \left(\tilde{k} - k_3 \rho_x^p - k_3 \delta_x^p \rho_x^p\right)\right] s_t \\ &- \left(k_3 + k_1 k_3 \delta_x^p + k_1^2 k_3 \delta_x^{p2}\right) a_{l,t} + k_1^3 E_{j,l,t} \overline{E}^{(2)} p_t. \end{aligned}$$

Continuing like this results in some infinite sums

$$
\begin{aligned}
p_{j,l,t} =& k\left(1+k_1+k_1^2+k_1^3\dots\right) \\
&- k_1k_3(1-\delta_x^p)\Big[1+k_1(1+\delta_x^p)+k_1^2(1+\delta_x^p+\delta_x^{p2})+k_1^3(1+\delta_x^p+\delta_x^{p2}+\delta_x^{p3}\dots)\Big]x_{t-1} \\
&+ \left[\tilde{k}+k_1\left(\tilde{k}-k_3\rho_x^p\right)+k_1^2\left(\tilde{k}-k_3\rho_x^p-k_3\delta_x^p\rho_x^p\right)+k_1^3\left(\tilde{k}-k_3\rho_x^p-k_3\rho_x^p\delta_x^p-k_3\rho_x^p\delta_x^{p2}\right)+\dots\right]s_t \\
&- k_3\left(1+k_1\delta_x^p+k_1^2\delta_x^{p2}+k_1^3\delta_x^{p3}\dots\right)a_{l,t}+k_1^\infty E_{j,l,t}\overline{E}^{(\infty)}p_t.
\end{aligned}
$$

For the terms in the third line, we have

$$
\begin{aligned}
&\tilde{k}+k_1\left(\tilde{k}-k_3\rho_x^p\right)+k_1^2\left(\tilde{k}-k_3\rho_x^p-k_3\delta_x^p\rho_x^p\right)+k_1^3\left(\tilde{k}-k_3\rho_x^p-k_3\rho_x^p\delta_x^p-k_3\rho_x^p\delta_x^{p2}\right) \\
&\quad +k_1^4\left(\tilde{k}-k_3\rho_x^p-k_3\rho_x^p\delta_x^p-k_3\rho_x^p\delta_x^{p2}-k_3\rho_x^p\delta_x^{p3}\right)\dots \\
=&\tilde{k}(1+k_1+k_1^2+k_1^3\dots)-\left(k_1k_3\rho_x^p+k_1^2k_3\rho_x^p+k_1^3k_3\rho_x^p\dots\right) \\
&\quad -\left(\delta_x^pk_1^2k_3\rho_x^p+\delta_x^pk_1^3k_3\rho_x^p+\delta_x^pk_1^4k_3\rho_x^p\dots\right)-\left(\delta_x^{p2}k_1^3k_3\rho_x^p+\delta_x^{p2}k_1^4k_3\rho_x^p+\delta_x^{p3}k_1^5k_3\rho_x^p\dots\right)\dots \\
=&\tilde{k}(1+k_1+k_1^2+k_1^3\dots)-k_1k_3\left(\frac{\rho_x^p}{1-k_1}+\frac{\rho_x^p\delta_x^pk_1}{1-k_1}+\frac{\rho_x^p\delta_x^{p2}k_1^2}{1-k_1}\dots\right) \\
=&\frac{\tilde{k}}{1-k_1}-\frac{k_1k_3\rho_x^p}{1-k_1}\left(1+\delta_x^pk_1+\delta_x^{p2}k_1^2\dots\right) \\
=&\frac{\tilde{k}}{1-k_1}-\frac{k_1k_3\rho_x^p}{(1-k_1)(1-\delta_x^pk_1)}.
\end{aligned}
$$

Proceeding similarly with the terms in the other lines results in

$$
p_{j,l,t}=\frac{k}{1-k_1}-\frac{k_1(1-\delta_x^p)}{1-k_1}\frac{k_3}{1-k_1\delta_x^p}x_{t-1}+\frac{1}{1-k_1}\left(\tilde{k}-\rho_x^p\frac{k_1k_3}{1-k_1\delta_x^p}\right)s_t-\frac{k_3}{1-k_1\delta_x^p}a_{l,t}+\underbrace{k_1^\infty\overline{E}_t^{(\infty)}}_{\to 0}p_t.
$$

Setting idiosyncratic technology shocks equal to zero in order to track the effects of aggregate shocks and observing that all firms then set the same price gives

$$
p_t\equiv\bar{k}_1+\bar{k}_2s_t+\bar{k}_3x_t,
$$

with

$$
\bar{k}_1=\frac{1}{1-k_1}\left[k-(1-\delta_x^p)\frac{k_1k_3}{1-k_1\delta_x^p}x_{t-1}\right]\quad\bar{k}_2=\frac{1}{1-k_1}\left(\tilde{k}-\rho_x^p\frac{k_1k_3}{1-k_1\delta_x^p}\right)\quad\bar{k}_3=-\frac{k_3}{1-k_1\delta_x^p}. \tag{A.8}
$$

To arrive at qualitative predictions for the impact of the structural shocks ε_t and e_t on output growth and the nowcast error, we need to determine the sign and the size of $\bar{k}_3$. Note that, according to (A.6),

$$-k_3 = \delta^h_{xp} \frac{k_2' - nk_3'/\delta^h_{xp} + k_2'(n-1)\delta^p_x}{n - (k_1' - k_2')},$$

where the first part of the numerator can be rewritten, by observing (A.5), as

$$k_2' - nk_3'/\delta^h_{xp} = \frac{1 - n/\delta^h_{xp} - \alpha}{\alpha + \gamma(1-\alpha)}.$$

Using (A.5) and (A.6) thus yields

$$-k_3 = \delta^h_{xp} \frac{(1-\alpha)[(n-1)\delta^p_x + 1] - n/\delta^h_{xp}}{(n-1)[\alpha + \gamma(1-\alpha)] + 1}.$$

Plugging this into the definition of $\bar{k}_3$ in (A.8) gives

$$\bar{k}_3 = \delta^h_{xp} \frac{\frac{(1-\alpha)[(n-1)\delta^p_x+1]-n/\delta^h_{xp}}{(n-1)[\alpha+\gamma(1-\alpha)]+1}}{1 - \delta^p_x \frac{(n-1)(\gamma-1)(1-\alpha)}{(n-1)[\alpha+\gamma(1-\alpha)]+1}}.$$

To obtain $\delta^h_{xp} = \delta^h_x + \delta^h_p$, we need to find the undetermined coefficients of equation (A.3). Start by comparing this equation with household l's expectation of equation (A.8):

$$E_{l,t}p_t = \underbrace{\bar{k}_1 + \bar{k}_3 x_{t-1}}_{\kappa^h_p w_t + \tau^h_p x_{t-1} - \eta^h_p r_t} + \underbrace{\left(\bar{k}_2 + \bar{k}_3 \rho^h_x\right)}_{\rho^h_p} s_t + \underbrace{\bar{k}_3 \delta^h_x}_{\delta^h_p} \hat{a}_{l,t}. \tag{A.9}$$

Hence, $\delta^h_{xp} = \delta^h_x(1 + \bar{k}_3)$. Inserting this into the above expression for $\bar{k}_3$ yields

$$\bar{k}_3 \equiv -\frac{n/\Upsilon - \delta^h_x \Psi}{\Phi - \delta^h_x \Psi}, \tag{A.10}$$

with

$$\Upsilon = (n-1)[\alpha + \gamma(1-\alpha)] + 1 > 0 \qquad \Psi = (1-\alpha)[(n-1)\delta^p_x + 1]/\Upsilon > 0$$
$$\Phi = 1 - \delta^p_x (n-1)(\gamma-1)(1-\alpha)/\Upsilon.$$

The signs obtain because $n > 1, 0 < \alpha < 1, \delta_x^p > 0$, and $\gamma > 1$. Observe that $\Psi\Upsilon < n$ because $\delta_x^p \leq 1$. Hence, $n/\Upsilon - \delta_x^h \Psi > 0$ because

$$n - \underbrace{\delta_x^h}_{>0,<1} \underbrace{\Psi\Upsilon}_{<n} > 0,$$

implying that the numerator of (A.10) is positive. Turning to the denominator $\Phi - \delta_x^h \Psi$, observe that $\Phi - \Psi > 0$. The denominator of (A.10) is therefore positive as well, and we have $\overline{k}_3 < 0$. Next, consider that $n/\Upsilon < \Phi$ and we obtain

$$-1 < \overline{k}_3 < 0.$$

This is a key result for the derivation of Propositions 1-3; see Appendix B. Multiplying the nominator and the denominator of the fraction in equation (A.10) by Υ and rewriting gives the expression used in Proposition 1.

Stage one of period t As information sets of agents are perfectly aligned during stage one, we use the expectation operator E_t to denote (common) stage-one expectations in what follows. Combining the results regarding expectations about inflation in period $t+1$ with the Euler equation, the Taylor rule, and the random-walk assumption for x_t gives

$$E_t y_t = E_t x_t - \psi E_t \pi_t.$$

Remember that the monetary policy shock emerges after wages are set. Its expected value before wage-setting is zero. Using $E_t x_t = E_t y_t$ (which results from combining labor supply and demand with the production function), we obtain

$$E_t \pi_t = 0.$$

Nominal wages are set in line with these expectations. We thus have determinacy of the price level. The central bank also expects zero inflation in the absence of monetary policy shocks. To find the effects of monetary policy shocks on the interest rate, including feedback effects via changes in expected inflation, note that, according to equation (A.9),

$$\overline{k}_1 + \overline{k}_3 x_{t-1} = \kappa_p^h w_t + \tau_p^h x_{t-1} - \eta_p^h r_t,$$

where, observing equations (A.5), (A.6), and (A.8),

$$\begin{aligned}\overline{k}_1 =& \frac{1}{(1-k_1)\Xi}\left[\frac{\alpha}{\alpha+\gamma(1-\alpha)} + k_2'\kappa_p^h\right] w_t - \frac{k_2'(1+\eta_p^h)}{(1-k_1)\Xi} r_t \\ &+ \frac{1}{(1-k_1)\Xi}\left\{k_2'(1+\tau_p^h) + k_2'\delta_{xp}^h\left[\frac{n-1}{n}(1-\delta_x^p) - 1\right] - \frac{(1-\delta_x^p)k_1k_3\Xi}{1-k_1\delta_x^p}\right\} x_{t-1}.\end{aligned}$$

We can hence determine the coefficient η_p^h as

$$-\eta_p^h = \frac{k_2'(1+\eta_p^h)}{(1-k_1)\Xi} = \frac{\alpha-1}{\alpha},$$

which is the impact of r_t on the price level. To finally determine the response of r_t, use this insight in the Taylor rule, resulting in

$$r_t = \psi\frac{\alpha-1}{\alpha} r_t + \nu_t = \frac{\alpha}{\alpha+\psi(1-\alpha)}\nu_t. \tag{A.11}$$

B Proofs

Proof of Proposition 1 Aggregating individual Euler equations (A.2) over all individuals, using (A.8), (A.9), and (A.11), gives

$$\begin{aligned}y_t =& E_{l,t}x_t + E_{l,t}p_t - p_t - r_t \\ =& x_{t-1} + \rho_x^h(1+\overline{k}_3)s_t + \left[\delta_x^h + \overline{k}_3(\delta_x^h - 1)\right]\varepsilon_t - \frac{\alpha}{\alpha+\psi(1-\alpha)}\nu_t \\ =& x_{t-1} + \underbrace{\rho_x^h(1+\overline{k}_3)}_{>0} e_t + \underbrace{\left[\delta_x^h + \rho_x^h - \overline{k}_3(1-\delta_x^h-\rho_x^h)\right]}_{>0}\varepsilon_t \underbrace{-\frac{\alpha}{\alpha+\psi(1-\alpha)}}_{<0}\nu_t,\end{aligned} \tag{B.1}$$

where $1-\delta_x^h-\rho_x^h > 0$ because of (A.1). Note that, if households have full information ($n \to \infty$), we get $\rho_x^h \to 0$ and $\delta_x^h \to 1$. Defining $\Omega \equiv -\overline{k}_3$, we can write

$$y_t = x_{t-1} + \rho_x^h(1-\Omega)e_t + \left[(\delta_x^h+\rho_x^h)(1-\Omega)+\Omega\right]\varepsilon_t - \frac{\alpha}{\alpha+\psi(1-\alpha)}\nu_t.$$

The signs indicated above result from $0 < \Omega = -\overline{k}_3 < 1$ (derived in Appendix A), completing the proof. ■

Proof of Proposition 2 Now consider the nowcast error, where expectations are either those of households or producers, that is, $E_{k,t}$ substitutes for either $E_{j,l,t}$ or $E_{l,t}$, and ρ^k, δ^k correspondingly for ρ^p, δ^p or ρ^h, δ^h. Taking expectations of equation (B.1) gives

$$\begin{aligned}E_{k,t}y_t =& x_{t-1} + \rho_x^h \left(1+\overline{k}_3\right) s_t + \left[\delta_x^h + \overline{k}_3(\delta_x^h - 1)\right] E_{k,t}\varepsilon_t - r_t \\ =& x_{t-1} + \left\{\rho_x^h(1+\overline{k}_3) + [\delta_x^h + \overline{k}_3(\delta_x^h - 1)]\rho_x^k\right\} s_t + \left[\delta_x^h + \overline{k}_3(\delta_x^h - 1)\right] \delta_x^k \varepsilon_t - r_t.\end{aligned}$$

$$\begin{aligned}y_t - E_{k,t}y_t =& -\rho_x^k \left[\delta_x^h + \overline{k}_3(\delta_x^h - 1)\right] s_t + \left[\delta_x^h + \overline{k}_3(\delta_x^h - 1)\right](1-\delta_x^k)\varepsilon_t \\ =& \underbrace{-\rho_x^k \left[\delta_x^h + \overline{k}_3(\delta_x^h - 1)\right]}_{<0} e_t + \underbrace{\left[\delta_x^h + \overline{k}_3(\delta_x^h - 1)\right]}_{>0} \underbrace{(1-\delta_x^k - \rho_x^k)}_{>0} \varepsilon_t,\end{aligned}$$

or

$$y_t - E_{k,t}y_t = -\rho_x^k \left[\delta_x^h(1-\Omega) + \Omega\right] e_t + \left[\delta_x^h(1-\Omega) + \Omega\right](1-\delta_x^k - \rho_x^k)\varepsilon_t.$$

The fact that $0 < -\overline{k}_3 < 1$ allows us to determine the signs of the effects of the shocks on the nowcast error. ■

Proof of Proposition 3 The model can be written in the following state-space system:

$$\begin{aligned}\tilde{X}_{t+1} &= C\tilde{X}_t + D\tilde{V}_t \\ \tilde{Y}_t &= F\tilde{X}_t + G\tilde{V}_t,\end{aligned}$$

with $\tilde{Y}_t$ and $\tilde{V}_t$ defined in the main text, $C = 0, D = I_3$, and

$$F = \begin{bmatrix} 0 & 0 & 0 \\ \frac{\Omega-1}{\alpha}(1-\alpha)(1-\rho_x^h - \delta_x^h) & \frac{1-\Omega}{\alpha}\rho_x^h(1-\alpha) & \frac{\alpha-1}{\alpha+\psi(1-\alpha)} \\ 0 & 0 & 0 \end{bmatrix}$$

$$G = \begin{bmatrix} \left[\delta_x^h(1-\Omega)+\Omega\right](1-\delta_x^k - \rho_x^k) & -\rho_x^k\left[\delta_x^h(1-\Omega)+\Omega\right] & 0 \\ \Omega + \frac{1-\Omega}{\alpha}\left[1-(1-\alpha)(\rho_x^h + \delta_x^h)\right] & \frac{\alpha-1}{\alpha}\rho_x^h(1-\Omega) & \frac{1-\alpha}{\alpha+\psi(1-\alpha)} \\ \frac{(\Omega-1)}{\alpha}(1-\delta_x^h - \rho_x^h) & \frac{1-\Omega}{\alpha}\rho_x^h & \frac{-1}{\alpha+\psi(1-\alpha)} \end{bmatrix}.$$

The dynamics of the model can then be represented by the following VAR (see Fernández-Villaverde et al. 2007 for details).

$$\tilde{Y}_{t+1} = F\sum_{j=0}^{\infty}(C - DG^{-1}F)^j DG^{-1}\tilde{Y}_{t-j} + G\tilde{V}_{t+1} = F\sum_{j=0}^{\infty}(-G^{-1}F)^j G^{-1}\tilde{Y}_{t-j} + G\tilde{V}_{t+1}.$$

The matrix FG^{-1} results as

$$FG^{-1} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1-\alpha \\ 0 & 0 & 0 \end{bmatrix},$$

such that

$$FG^{-1}FG^{-1} = 0$$

and we obtain the final VAR(1) representation[34]

$$\tilde{Y}_{t+1} = \underbrace{FG^{-1}}_{\equiv A}\tilde{Y}_t + \underbrace{G}_{\equiv B}\tilde{V}_{t+1}.$$

■

Proof of Corollary 1 Using the equations derived in the proof of Proposition 3, the long-run impact matrix—showing the effect of the shocks on the accumulated variables—can be calculated as $(I_3 - FG^{-1})^{-1}G$, that is

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1-\alpha \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \left[\delta_x^h(1-\Omega)+\Omega\right](1-\delta_x^k-\rho_x^k) & -\rho_x^k\left[\delta_x^h(1-\Omega)+\Omega\right] & 0 \\ \Omega + \frac{1-\Omega}{\alpha}\left[1-(1-\alpha)(\rho_x^h+\delta_x^h)\right] & \frac{\alpha-1}{\alpha}\rho_x^h(1-\Omega) & \frac{1-\alpha}{\alpha+\psi(1-\alpha)} \\ \frac{(\Omega-1)}{\alpha}(1-\delta_x^h-\rho_x^h) & \frac{1-\Omega}{\alpha}\rho_x^h & \frac{-1}{\alpha+\psi(1-\alpha)} \end{bmatrix}$$
$$= \begin{bmatrix} * & * & 0 \\ 1 & 0 & 0 \\ * & * & * \end{bmatrix},$$

where asterisks represent non-zero elements. The middle row captures the long-run impact of the shocks on the level of labor productivity, as labor productivity enters in first differences. The short-run impact of ν_t on the nowcast error equals the upper-right entry of G; it is zero. ■

[34]Note that the "poor man's invertibility condition" of Fernández-Villaverde et al. (2007) is satisfied as the matrix $-G^{-1}F$ has rank one and therefore, at most, one non-zero eigenvalue. The trace equals zero, such that all eigenvalues are zero and hence strictly less than unity.

C Monte Carlo assessment of the VAR

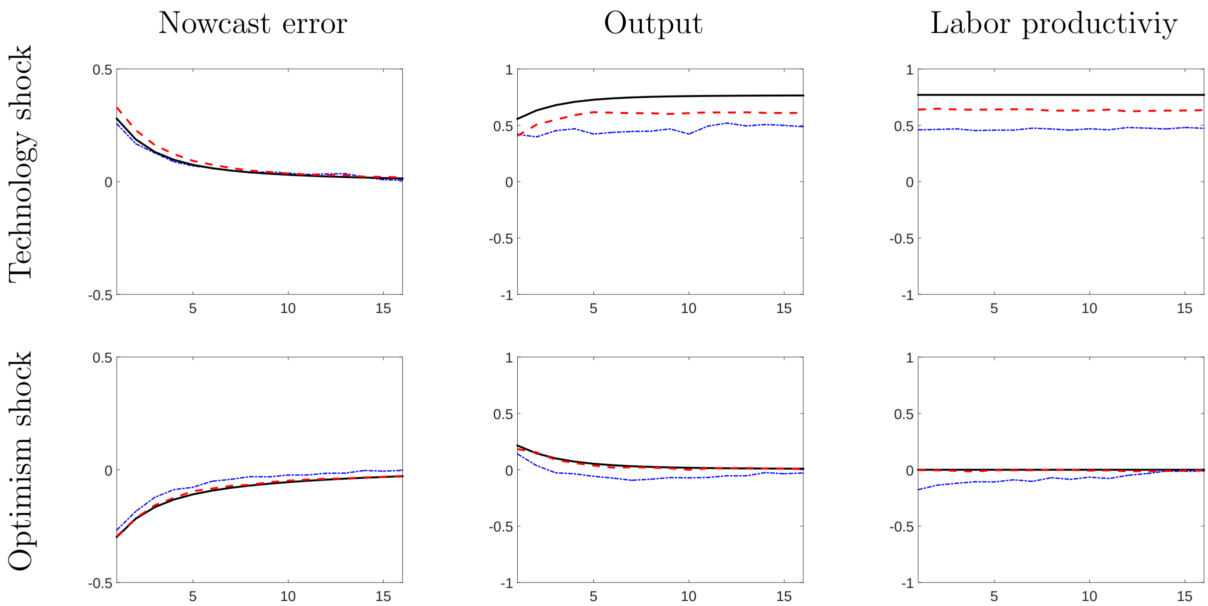

Figure C.1: Impulse responses to one-standard-deviation shock under baseline identification: model vs. estimation (Monte Carlo). Notes: Black line represents true response; sample comprises 128 (blue dashed-dotted line) or 1000 (red dashed line) observations, both lines are medians over 100 point estimates each. VAR specification as in baseline (see Section 4), without trend. Model corresponds to dispersed-information setup of Lorenzoni (2009), with interest-rate shock added to the Taylor rule (volatility set according to estimates by Smets and Wouters 2007).