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Growth Expectations, Undue Optimism, and Short-Run Fluctuations

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Growth Expectations, Undue Optimism, and Short-Run Fluctuations

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Growth Expectations, Undue Optimism, and Short-Run Fluctuations

Abstract

We assess the contribution of “undue optimism” (Pigou) to short-run fluctuations. In our analysis, optimism pertains to total factor productivity which determines economic activity in the long run, but is not contemporaneously observed by market participants. In order to recover optimism shocks - autonomous, but fundamentally unwarranted changes in the assessment of productivity - from actual time series, we rely on an informational advantage over market participants. Specifically, we compute the nowcast error regarding current output growth drawing on the Survey of Professional Forecasters. Including nowcast errors in a vector autoregression model makes it possible to identify optimism shocks. Optimism shocks, in line with theory, induce a negative nowcast error but raise economic activity in the short run. They account for up to 30 percent of short-run fluctuations.

JEL-Code: E320.

Keywords: undue optimism, optimism shocks, noise shocks, animal spirits, business cycles, nowcast errors, VAR, long-run restrictions.

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1 Introduction

Economic outcomes depend on expectations and vice versa. In this paper, we ask to what extent changes of expectations are an *autonomous* source of business cycle fluctuations. This question dates back to Pigou (1927) who discusses the possibility that “errors of undue optimism or undue pessimism” are a genuine 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 productivity. Lorenzoni (2009), in turn, puts forward a model in which misperceptions regarding the current state of productivity turn out to be an important source of business cycle fluctuations.

In this paper, we take up the issue empirically and investigate the contribution of undue optimism and pessimism to business cycles fluctuations. Estimating a vector autoregression (VAR) on U.S. time-series data, we seek to identify “optimism shocks”, that is, changes in expectations due to a perceived change in total factor productivity which does not actually materialize. Blanchard et al. (2012) show that this constitutes a formidable challenge, because optimism shocks or, quite generally, misperceptions are mistakes of market participants. As such they cannot be uncovered on the basis of standard time-series techniques. Instead, one may resort to estimating fully specified general equilibrium models (Barsky and Sims 2012) or exploit information not available to market participants in real time.

Our analysis is based on this insight. Specifically, our identification strategy relies on an *ex-post* measure of agents’ misperceptions, namely the nowcast error regarding current output growth. Drawing on the Survey of Professional Forecasters (SPF), we compute it as the difference between actual output growth in a given quarter and the median of the predicted values in real time. A positive realization of the nowcast error thus implies that nowcasts have been too pessimistic. Yet it is important to keep in mind that, as a reduced-form measure, nowcast errors may be the result not only of optimism shocks, but of various structural innovations.

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. Nevertheless, as we show in the first step of our analysis, nowcast errors can be sizable. Depending on whether we consider the first or the final release of data for actual output growth, the largest nowcast error exceeds 1 or 1.75 percentage points of quarterly

¹Keynes’ 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 and 162).

output growth respectively. We also document that nowcast errors are positively correlated with economic activity and investigate the effect of well-known measures of structural innovations on nowcast errors. We find that innovations which are publicly observable, such as monetary and fiscal policy shocks or uncertainty shocks, do not cause nowcast errors. In contrast, productivity shocks have a significant effect on nowcast errors, presumably because they impact current output growth, but are not observable in real time.

Nowcast errors play a key role in our analysis as they allow us to recover optimism shocks from actual time series data. We establish this result within a business cycle model which mimics, in a stylized way, the informational friction which 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. Using the model, we also derive the identification restrictions on which we rely in the main part of our analysis. Specifically, drawing on earlier work by Galí (1999) and others, we estimate a VAR model on time-series data for labor productivity, employment, and the nowcast error. In order to identify the distinct contributions of optimism and productivity shocks to short-run fluctuations, we assume, in line with our theoretical results, that nowcast errors may emerge only as a result of optimism or productivity shocks. Yet optimism shocks, in contrast to productivity shocks, have no bearing on labor productivity in the long run.

According to the estimated VAR model, optimism shocks—as predicted by theory—induce a *negative* nowcast error, yet significantly boost economic activity at the same time. This result is noteworthy, because we do not restrict the response of the nowcast error to optimism shocks. Moreover, as the unconditional correlation between nowcast errors and economic activity is positive, the change of the correlation conditional on optimism shocks lends additional support to our identification strategy. Instead, productivity shocks induce a *positive* nowcast error while also stimulating economic activity. These results are robust across a range of alternative specifications, including alternative measures of the nowcast error. Finally, computing a forecast error variance decomposition, we find that optimism shocks account for up to 30 percent of output fluctuations.

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 (2012) develop a model where “sentiment shocks” arise, as 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. A number of contributions have focused on the distinction between current and anticipated productivity shocks. Evidence by 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. In any case, to the extent that anticipated shocks do not materialize as expected, a recession might ensue, which is thus caused by undue optimism (Jaimovic and Rebelo 2009). In our analysis, we allow misperceptions to pertain also to current, instead of only to future productivity.

We also stress that there are few attempts to identify optimism shocks empirically without imposing a fully structural model on the data. Blanchard (1993) provides an animal-spirits account of the 1990–91 recession focusing on consumption. Carroll et al. (1994) show that consumer sentiment forecasts consumption spending—aside from the information contained in other available indicators. Yet in concluding they suggest a “fundamental explanation” based on habits and precautionary saving motives. Oh and Waldman (1990) show that “false macroeconomic announcements”, identified as measurement error in early releases of leading indicators, cause future economic activity. They refrain from a structural interpretation, however. 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, Bachmann and Sims (2012) explore the importance of confidence for the transmission of fiscal shocks, but do not analyze the effect of exogenous variations in confidence.

The remainder of the paper is organized as follows: The next section introduces our measure of nowcast errors and provides a number of statistics illustrating their properties. Section 3 puts forward a simple model which allows us to clarify issues pertaining to the notion of optimism shocks and their identification. Section 4 presents our VAR model and results. A final section concludes.

2 A reduced-form measure of misperceptions

We eventually aim to uncover the effects of *optimism shocks*, that is, a perceived change in productivity which does not actually materialize. In this section, as a 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 other structural innovations. Still, nowcast errors will play a key role in our identification strategy in Section 4 below. In what follows, we therefore 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 survey is conducted at quarterly frequency. Panelists receive the questionnaires at the end of the first month of the quarter and have to submit their answers by the 2nd to 3rd week of the following month. The results of the survey are released immediately afterwards. At this stage, no information regarding current output is available from the Bureau of Economic Analysis (BEA). 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.

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. We compute nowcast errors by subtracting the survey’s median forecast from the actual value reported later by the BEA.³ We compute two measures of nowcast errors by distinguishing between the first and the final data release for actual output growth.⁴ For the latter, we use the latest available data vintage. We thereby address concerns that the assessment of nowcasts or, more generally, forecasts depends on what is being used as the “actual” or realization (see, e.g., Stark and Croushore 2002).⁵

2.2 Nowcast errors

We compute nowcast errors as the difference between actual output growth in a given quarter and the median value of the predicted value. They are shown in the left panel of Figure 1, measured in annualized percentage points. The solid (dashed) line represents results based on first-release (final-release) data. Although the two series co-move strongly (correlation: 0.55), there are perceptible differences. For instance, there are sizable negative errors in the

²Professional 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 2012Q4, 39 forecasters participated in the survey.

³For 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 forecast of the quarterly growth rate of real output, seasonally adjusted at annual rate (real GNP prior to 1992 and real GDP afterwards). Also note that prior to 1981Q3 the SPF asks for nominal GNP only. In this case, the forecast for the price index of GNP is applied to obtain the implied forecast for real GNP.

⁴Data are obtained from BEA and the Philadelphia Fed’s Real-time Data Set for Macroeconomists. First-release data: BEA’s first (advance) estimate of the quarterly growth rate of real GNP/GDP (seasonally adjusted at annual rate, with real GNP prior to 1992 and real GDP for 1992-present): ROUTPUT. Final-release data: series GNPC96 and GDPC96 which are quarterly Gross National/Domestic Product, seasonally adjusted at annual rates, chained 2005 Dollars.

⁵In fact, the authors consider a set of alternative definitions of actuals and find statistically significant differences of forecast evaluations for real output. We show below, however, that our results hold independently of the choice of first- or final-release data.

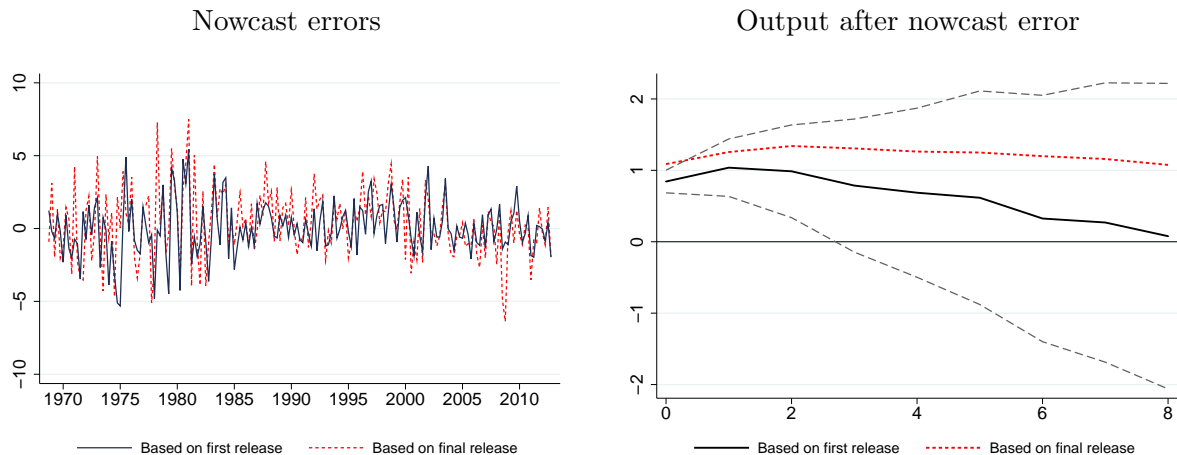


Figure 1: Nowcast error. Left panel: series based on first-release data (solid) and final-release data (dashed). Errors are measured in annualized percentage points (vertical axis). Right panel: cumulative impulse response of output growth to nowcast error based on local projections. Horizontal axis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

second half of 2008 only for the measure based on final-release data. Presumably, at the beginning of the great recession the actual growth slowdown was larger not only relative to what professional forecasters predicted in real time, but also relative to what initial data suggested. Moreover, errors based on first-release data are shifted downwards relative to those based on final-release data, notably in the first half of the sample.

This is confirmed by the summary statistics reported in Table 1: the mean of the nowcast errors is significantly positive if we consider final-release data, but not significantly different from zero in the case of first-release data. The standard error and the largest realizations of the nowcast error are also considerably larger in the case of final-release data.⁶ The difference is likely due to the revision process of the statistical office and particularly to benchmark revisions. We therefore rely on first-release data in our baseline VAR model in section 4, and consider final-release data in our sensitivity analysis. Finally, the last two columns of Table 1 report results of a Ljung–Box test, suggesting that there is no serial correlation in both series. What causes nowcast errors? Assuming that the average forecaster has a correct understanding of the economy, structural innovations that are public information should not induce systematic forecast errors. On the other hand, structural innovations that are not directly observable may generate nowcast errors. To assess this hypothesis, we run regressions of

⁶This finding is consistent with evidence provided by Faust et al. (2005) regarding GDP announcements. For G7 countries it turns out that revisions of initial announcements are significantly positive on average in their sample period. Note, however, that the mean of final-release nowcast errors becomes insignificant once we control for productivity shocks below.

Table 1: Summary statistics nowcast errors

	N	Mean	SD	Min	Max	Ljung–Box test	
						Q-stat.	p-value
Final-release based	177	.35**	2.36	-6.38	7.49	2.59	.96
First-release based	177	.04	1.86	-5.31	5.43	8.68	.37

Notes: Nowcast errors computed on the basis of final-release (top row) and first-release (bottom row) data, measured in annualized percentage points; sample: 1968Q4 - 2012Q4. Means are tested against zero based on a standard t-test. ‘**’ indicates significance at the 5% level. The last two columns report Q-statistics and p-values for a Ljung-Box test assessing the null hypothesis of zero autocorrelations up to 8 lags.

nowcast errors on popular (and relatively uncontroversial) series of structural innovations. Specifically, we consider monetary policy shocks identified by Romer and Romer (2004), tax shocks identified by Romer and Romer (2010), uncertainty shocks identified by Bloom (2009), and productivity shocks provided by Fernald (2012).⁷

In each instance, we regress nowcast errors on the contemporaneous realization of the structural shock, while also including four lags of the nowcast error in the regression model. The sample varies across regressions, since we use the longest overlapping sample in each case. Results for the impact effect are reported in Table 2. Newey-West standard errors are reported in parentheses. The top row reports results based on the final-release data, the bottom row is based on the first-release data. We find that for monetary and fiscal policy innovations, as well as for uncertainty shocks, there is indeed no significant impact on nowcast errors, in line with the hypothesis that the effect of observable innovations is relatively well understood by forecasters. Instead, it is productivity innovations that have a significant impact. Specifically, positive productivity innovations tend to raise the nowcast error contemporaneously, that is, they tend to raise the growth of economic activity beyond the expected level.

⁷Following Basu et al. (2006), Fernald constructs a utilization-adjusted series of TFP at quarterly frequency. In terms of actual series we use the “utilization-adjusted TFP in producing non-equipment output” (dtfp_C_util) of Fernald (2012). For the 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). In the case of monetary and tax shocks we use the quarterly average of the monthly shock series (RESID) and the “sum of Deficit-Driven and Long-Run Tax Changes” (EXOGENRRATIO) of Romer and Romer (2004) and Romer and Romer (2010) respectively.

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

	Monetary Policy 1969:1 - 1996:4	Taxes 1968:4 - 2007:4	Uncertainty 1963:3 - 2008:2	Productivity 1968:4 - 2009:3
Final-release based	1.678 (1.044)	-.002 (1.144)	.451 (.435)	.480*** (.049)
First-release based	1.611 (.978)	-.730 (.963)	.088 (.260)	.140*** (.045)

Notes: Impact effect on nowcast error obtained from regressing the nowcast error on the time series for the structural innovations to monetary policy, fiscal policy (taxes), uncertainty, and productivity. The regression includes four lags of the nowcast error. Newey-West standard errors robust for autocorrelation up to four lags are reported in parentheses; time series of structural innovations to monetary policy, taxes, uncertainty, and productivity provided by Romer and Romer (2004), Romer and Romer (2010), Bloom (2009), and Fernald (2012) respectively.

2.3 Nowcast errors and economic activity

Nowcast errors are positive surprises regarding current activity. They are also positively correlated with output growth.⁸ To explore systematically how current nowcast errors relate to economic activity, we estimate the dynamic relationship on the basis of local projections (see Jordà 2005). In particular, we relate current and future output growth to current nowcast errors.⁹

The right panel of Figure 1 shows the cumulative impulse response of output growth to a nowcast error. The horizontal axis measures quarters, the vertical axis percentage deviation of output from the constant-growth path. Dashed lines indicate 90 percent confidence bounds implied by Newey-West standard errors. We find that nowcast errors predict a strong, mildly hump-shaped increase of economic activity. The effect is stronger for our measure based on the final-release data, yet differences are moderate relative to the one based on first-release data. The finding that (reduced-form) nowcast errors predict future activity is noteworthy in light of the results regarding effects of optimism shocks documented in Section 4 below. Before discussing this evidence, we provide a theoretical rationale for our empirical framework in the following section.

⁸The correlation between GDP growth (final-release data) and the nowcast error is .73 and .47 for the final-release and first-release measure respectively.

⁹To capture potential serial correlation, we apply Newey-West standard errors. 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.

3 The model

In this section we put forward a model which allows us to formally define optimism shocks, discuss conditions under which they may affect economic activity and, importantly, clarify issues pertaining to identification. 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), a key feature of which is that agents do not observe current output. 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.

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 $1 < n < \infty$.¹⁰ Households have an infinite planning horizon. Producers produce differentiated products on the basis of an island-specific productivity, which is determined by a permanent, economy-wide component and a temporary, idiosyncratic component. 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. Finally, the central bank sets the interest rate based on expected inflation.

Shocks realize during the second stage. We distinguish between shocks which are directly observable and shocks which are not. Optimism and productivity shocks fall in the latter category. In particular, information about idiosyncratic productivity is private to each producer. Additionally, all agents observe a signal about average productivity. While the signal is unbiased, it contains an i.i.d. zero-mean component: the optimism shock.¹¹ In terms of observable shocks, we allow for monetary policy shocks. Yet, rather than being interested in the effects of monetary policy shocks per se, we merely aim at contrasting the effects of ob-

¹⁰This setup ensures that households cannot infer aggregate productivity exactly from observed prices. At the same time, individual producers have no impact on the price of households' consumption baskets.

¹¹We refer to this signal component throughout as an "optimism shock" with the understanding that realizations may be positive (optimism shock) or negative (pessimism shocks).

servable shocks on nowcast errors to those of non-observable shocks. 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 is 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 maximizes lifetime utility given by

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

with $E_{l,t}$ being the expectation operator based on household l 's information set at the time of its consumption decision (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

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

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 $C_{j,m,l,t}$. $\Pi_{j,l,t}$ are profits of firm j on island l and $\varrho_{l,t,t+1}$ is household l 's stochastic discount factor between t and $t+1$. At the beginning of the period, the household receives a payoff $A_{l,t-1}$ from its portfolio of state-contingent securities, purchased in the previous period. $B_{l,t}$ are state non-contingent bonds paying an interest rate of r_t . A complete set of state-contingent securities is traded at the beginning of the period, while state non-contingent bonds can be traded via the central bank throughout the entire period.¹² 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

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

¹²As a result, households cannot extract additional information about aggregate variables from the prices of the securities.

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

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

3.3 Producers and monetary policy

The central bank follows a standard Taylor rule but sets the net interest rate r_t before observing prices, that is during stage one of period t :

$$r_t = \psi E_{cb,t} \pi_t + \theta_t \quad \psi > 1,$$

where π_t is economy-wide net inflation, calculated on the basis of all goods sold in the economy. The expectation operator $E_{cb,t}$ conditions on the information set of the central bank, which consists of information from period $t - 1$ only.¹³

θ_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

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

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 based on a combination of private and public information (see below). Given prices, the level of production is determined by demand during stage three.

3.4 Productivity and signal

Log-productivity on each island, denoted by small-case letters, 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

$$\Delta x_t = \varepsilon_t.$$

¹³Pre-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 setup without changing its qualitative predictions. Pre-set wages, on the other hand, guarantee determinacy of the price level. They do not affect output dynamics after optimism and productivity shocks, because good prices may still adjust.

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 (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 which 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 from her price. 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 and depend on $n, \sigma_e^2, \sigma_\varepsilon^2$, and σ_η^2 . 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 $n \rightarrow \infty$.

3.5 Market clearing

Good and labor markets clear in each period:

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

where $C_{j,m,l,t} = 0$ if household l does not visit island m . The asset market clears by 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. 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 ($\theta_t < 0$) raise output. Formally, we have*

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

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

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. Formally,*

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

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 setting, the deviation from the expected average price level is subdued. Consumers, in turn, observe higher prices. They too attribute this increase to adverse 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. Because the observed price increase relative to the expected long-run price level is muted, expenditure and, consequently, economic activity expand. 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.¹⁴

After a productivity shock, on the other hand, producers do not fully trust the signal about the aggregate component and attribute some of the increased productivity to idiosyncratic factors. They lower prices below what they expect the average price level to be. Consumers expect higher income and 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.

¹⁴As 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.

Furthermore, observe 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 to productivity, or incorrect signals regarding productivity.

3.7 Identification

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

$$\tilde{Y}'_t = \begin{bmatrix} \Delta y_t - E_{k,t} \Delta y_t & \Delta(y_t - l_t) & l_t \end{bmatrix},$$

we obtain the following proposition.

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

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

and the matrices A and B are given in the proof.

Intuitively, we are able to cast the model dynamics in VAR form because we rely on variables that are not contemporaneously observed in the model. 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. (2012), 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 sizeable. 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.*

4 The effects of optimism shocks

We are now in a position to identify the effects of optimism shocks in actual time-series data and to quantify their contribution to U.S. short-run fluctuations. We do so within an estimated VAR model, combining long-run restrictions (see, for instance, Galí 1999) and short-run restrictions, which we impose on nowcast errors. Including a time series of nowcast errors in the VAR model is key to our identification strategy. It represents an informational advantage over market participants and allows us to isolate optimism and productivity shocks. In the following, we discuss our VAR specification and identification strategy before turning to the results.

4.1 VAR specification

Our VAR model includes three variables. Under the baseline specification we include the nowcast error computed on the basis of first-release data, the growth rate of labor productivity, and hours worked in the vector of endogenous variables.¹⁵ Formally, as \tilde{Y}_t is the vector containing these variables in the given order, the VAR model in reduced form reads as

$$\tilde{Y}_t = \sum_{i=1}^L A_i \tilde{Y}_{t-i} + \nu_t, \quad (4.1)$$

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

Regarding the number of lags L , we account for concerns about a lag-truncation bias. Arguably, it is particularly severe in the case that long-run restrictions are imposed on the VAR model to achieve identification (Chari et al. 2008). De Graeve and Westermarck (2013)

¹⁵Labor productivity is measured by (the first difference of the natural logarithm of) output per hour of all persons in the nonfarm business sector and hours worked is the natural logarithm of the corresponding hours. Both series are obtained from the Bureau of Economic Analysis. Results are robust, however, once we measure labor productivity as output per person and hours as employment, both obtained from the Bureau of Labor Statistics.

¹⁶Below, we additionally consider alternative trend specifications to address the potential non-stationarity of the time series for hours worked.

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

perform Monte Carlo experiments and find that raising the number of lags may be a viable strategy to reduce the severity of the problem. Hence, for our baseline specification we set $L = 8$. We document below that the results are robust with respect to using a smaller number of lags.

We aim to identify structural shocks contained in the vector, ϵ_t , with $\nu_t = B\epsilon_t$ and $E\epsilon\epsilon' = I$. Given estimates for Ω and the A_i matrices, we identify B by simultaneously imposing short and long-run restrictions. Without loss of generality, we assume that ϵ_t contains from top to bottom the productivity shock, the optimism shock, and a third shock to which we do not attach any structural interpretation. Key to our identification strategy is the insight that nowcast errors can only be the result of the first two shocks—both in the short and the long run. To tell productivity and optimism shocks apart, we impose as a third restriction that optimism shocks do not impact labor productivity in the long run. All restrictions are consistent with the model developed in the previous section (see Corollary 1). Formally, our identification assumptions impose the following restrictions on the matrices B and A_0 , which determine the contemporaneous and the long-run impact, respectively:

$$B = \begin{bmatrix} * & * & 0 \\ * & * & * \\ * & * & * \end{bmatrix}, \quad A_0 \equiv \left(I - \sum_{i=1}^L A_i \right)^{-1} B = \begin{bmatrix} * & * & 0 \\ * & 0 & * \\ * & * & * \end{bmatrix}. \quad (4.2)$$

4.2 Results

We compute impulse response functions on the basis of the estimated model and display results in Figure 2. The columns (from left to right) display the responses to a productivity shock, an optimism shock, and the third shock. Solid lines represent the point estimate, while dashed lines indicate 90 percent confidence bounds obtained by bootstrap sampling. The rows display the responses of the nowcast error, output (implied by those of labor productivity and hours), labor productivity, and hours respectively. In each case, horizontal axes measure time in quarters, while vertical axes measure percentage points in the case of the nowcast error and percentage deviations from steady state otherwise. To facilitate the comparison of productivity and optimism shocks, we consider in each case an expansionary shock which triggers an increase of output and normalize its size such that it induces a nowcast error equal to 1 percentage point (annualized) in absolute value.

A first noteworthy result is the joint responses of the nowcast error and output to both structural shocks. While output rises in each instant, we find that productivity shocks induce a positive response of the nowcast error and optimism shocks induce a negative response. This finding is in line with the prediction of the model developed in Section 3 above, even

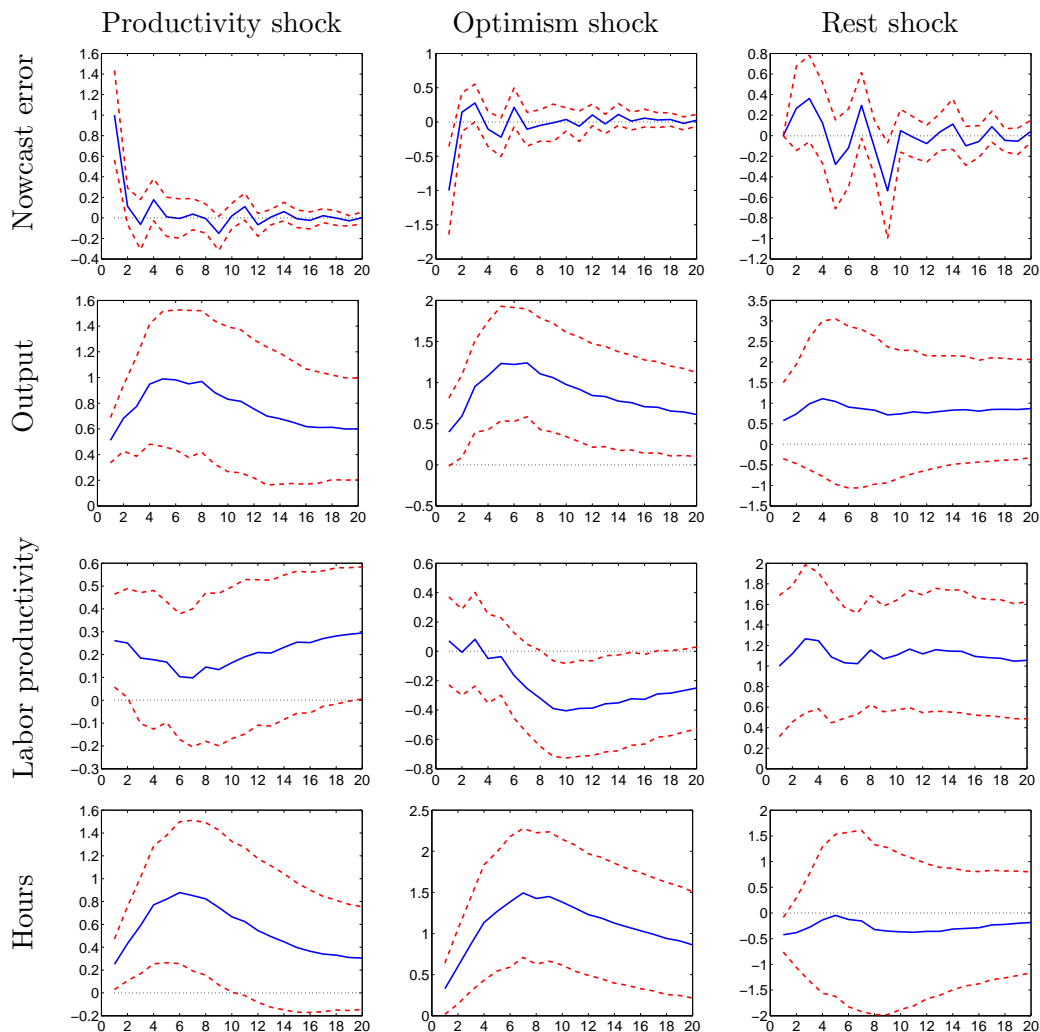


Figure 2: Impulse responses to identified shocks. *Notes:* baseline VAR model; solid lines indicate point estimates, dashed lines 90 percent confidence bounds obtained by bootstrap sampling (1000 repetitions). Horizontal axes measure quarters. Vertical axes: percentage points in the case of the nowcast error, percent otherwise.

though the response of the nowcast error to both shocks has been left unrestricted. More generally, the finding that optimism shocks induce a negative co-movement of the nowcast error and output is remarkable because the unconditional co-movement of both series is positive, as established in Section 2. In our view, the result that the co-movement changes from unconditionally positive to negative conditional on optimism shocks 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 quite persistent and displays hump-shaped adjustment dynamics. In fact, the short-run dynamics are fairly similar in both instances. The impact increase is approximately 0.5 percent and the peak response is reached after about 6 quarters. While the peak response is

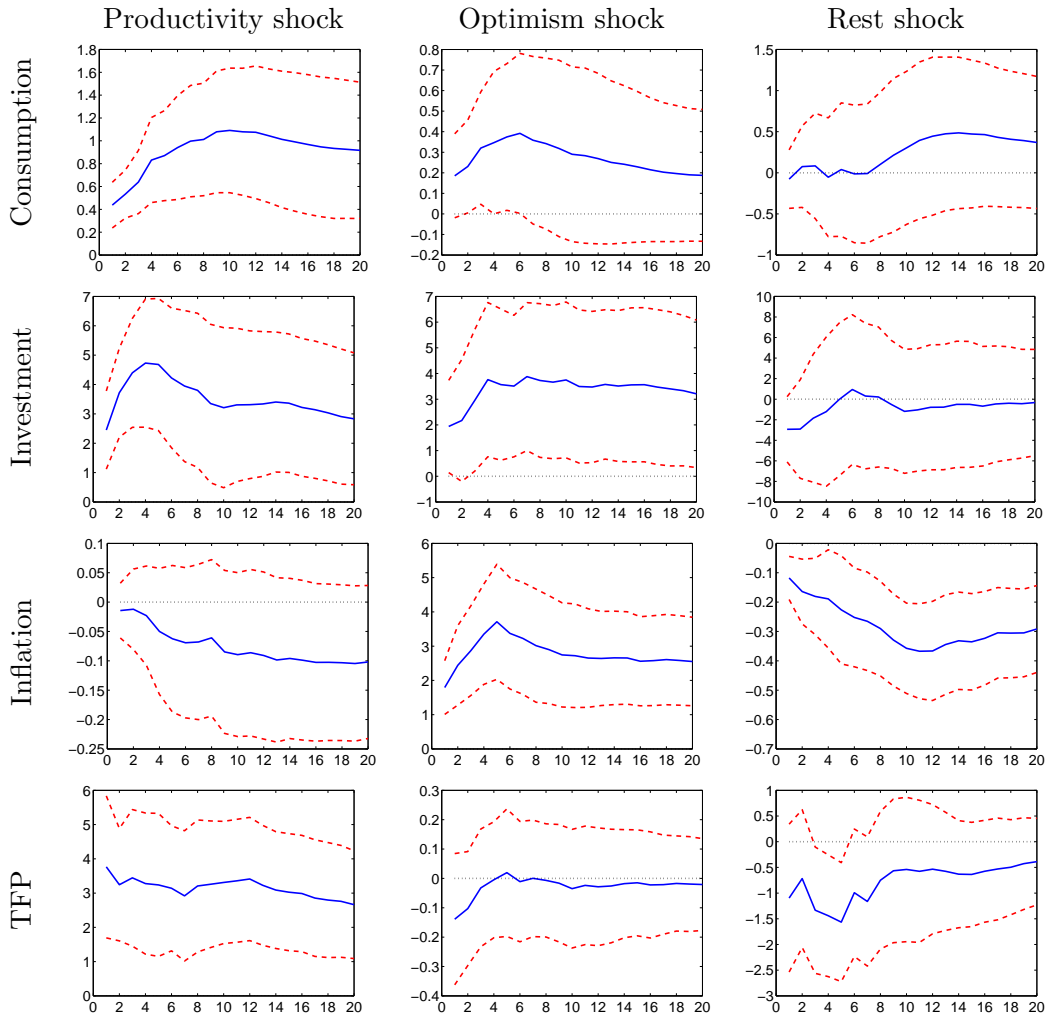


Figure 3: Impulse responses to identified shocks. *Notes:* each row displays the response of an additional variable replacing hours in the baseline VAR model (see Figure 2).

somewhat stronger in the case of an optimism shock, the response is more persistent in the case of a productivity shock, even though we still find the output response to an optimism shock marginally significant after 20 quarters. The third row shows the response of labor productivity. It increases in response to a productivity shock on impact, but also in the long run. In line with theory, productivity declines in response to an optimism shock, but the effect is only marginally significant. Note that optimism shocks are not allowed to impact labor productivity in the long run under our identification scheme.

The responses of hours are shown in the last row. In the short run the responses mimic that of output. It is somewhat weaker in the case of productivity shocks and somewhat stronger in the case of optimism shocks, reflecting the differential effect of these shocks on labor productivity. In the long run hours are back to the pre-shock level. In order to contrast the

transmission of optimism shocks to those of productivity shocks it is of interest to investigate their effects on variables other than those included in the baseline model. To estimate the impulse responses of these variables while economizing on the degrees of freedom, we rotate additional variables into our baseline VAR model, replacing the time series for hours worked. Figure 3 displays results for four additional variables of particular interest. The first two rows show the responses of consumption and investment respectively.¹⁸ Applying the same normalization as above, we find that productivity and optimism shocks raise consumption and investment, although the effect is somewhat stronger and more persistent in the case of productivity shocks.

The third row of Figure 3 shows the response of core CPI inflation. We find that productivity shocks tend to be deflationary, although the response is not significant. Instead, inflation rises immediately and strongly in response to the optimism shock. Optimism shocks accordingly have the flavor of what has been traditionally referred to as a demand shock (Lorenzoni 2009). Finally, in the last row, we show the response of a direct measure of total factor productivity. Investigating its response to productivity shocks helps to assess the plausibility of our identification scheme, which relies on the absence of a long-run impact of optimism shocks on labor productivity. The time series for total factor productivity is obtained from Fernald (2012), as in Section 2 above.¹⁹ Since it ends in 2009Q3, we estimate the VAR model on the longest available data series (1968Q4–2009Q3). The impulse responses show a strong increase of TFP to the productivity shock identified on the basis of long-run restrictions, but no reaction to optimism shocks—in line with the assumptions underlying our identification strategy.

Overall, we find plausible results regarding the effects of optimism shocks and thus turn to the question that motivates our analysis: namely, to what extent are optimism shocks 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. We find that productivity and optimism shocks are responsible for two thirds and one third of the variation in the nowcast error respectively. This finding holds irrespective of the forecast horizon. Recall that in the short and long run nowcast errors are restricted to be driven only by these two shocks. Regarding output, productivity shocks account for the bulk of fluctuations, yet optimism shocks also contribute substantially. In the short run their contribution rises from 17 percent to almost one third after about three years, declining thereafter.

¹⁸Consumption is measured by real personal consumption expenditures and investment by real gross private domestic investment, both from the Bureau of Economic Analysis.

¹⁹Inflation is based on the consumer price index for all urban consumers for all items less food and energy from the Bureau of Labor Statistics, and TFP is utilization-adjusted TFP in producing non-equipment output of Fernald (2012).

Table 3: Forecast error variance decomposition

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

Notes: Results are presented for the baseline VAR model. Each panel reports the decomposition of the forecast error variance for the variable of interest, considering a forecast horizon of 1, 4, 12 and 40 quarters. The contribution of the three shocks is reported in the appropriately labeled columns.

These findings are in a similar order of magnitude than those reported by Blanchard et al. (2012). 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 account for about 20 percent of output volatility.²⁰ Instead, Barsky and Sims (2012), estimating a fully specified DSGE model through 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 to consumer confidence, which they find to reflect news rather than animal spirits. Once we rotate their time series of confidence innovations as a third variable into our VAR model, we find it to be

²⁰In a similar exercise, Hürtgen (2013) obtains a value of 14 percent.

mostly driven by the “rest” shock.²¹ This finding is consistent with the results of Barsky and Sims (2012) insofar as the rest shock will pick up anticipated productivity shocks under our identification scheme.

4.3 Sensitivity analysis

We conduct a number of experiments to explore the robustness of our results. First, we consider alternative measures of the nowcast error, which is key to our identification strategy. Our baseline VAR is estimated on nowcast errors computed on the basis of first-release data. Results in Section 2 suggest that nowcast errors based on final-release data may differ somewhat. We therefore estimate our VAR model while replacing the first-release nowcast error with the final-release nowcast error. The estimated impulse responses to productivity and optimism shocks obtained under this specification are shown in the left panel of Figure 4, confirming our findings for the baseline VAR model reported in Figure 2. In what follows we explore to what extent results are robust once we consider a different sampling frequency, as our identification strategy relies on assumptions regarding the available information at the time forecasters are asked to predict current output growth. Specifically, forecasters are assumed to have no information regarding current innovations to productivity. Due to the frequency of 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 an appropriate survey of professional forecasters by Bloomberg.²² Results are shown in the right panel of Figure 4. From a qualitative point of view, they are in line with those obtained for the baseline VAR model, despite considerable differences in the sample (1996M10–2012M12), data frequency, and the measure of economic activity.

Next, we are turning to alternative assumptions regarding our sample and the number of lags included in the VAR model. Results are shown in Figure 5. The left panel shows results for the longest possible sample given data availability: 1968Q4–2012Q4. They are very similar

²¹Specifically, we consider the series for confidence innovations of Barsky and Sims (2012), which is based on the Michigan Survey of Consumers. Confidence innovations are computed on the basis of their VAR model and their orthogonalization with confidence ordered first. We include confidence innovations in our baseline VAR model (using the longest overlapping sample), replacing the time series for hours worked. Computing a forecast error variance decomposition, we find that about two thirds of the short-run variance of confidence innovations is due to the rest shock, while the optimism shock accounts for less than 5 percent. Moreover, we find that only the rest shock has a significant impact on confidence innovations. It is positive and short-lived.

²²The Bloomberg survey forecasts are available since 1996M10. We consider data up to 2012M12. The series on monthly hours is the index of aggregate weekly hours of production for workers in manufacturing from the Bureau of Labor Statistics, while the corresponding growth rate of labor productivity is the difference in the growth rates of the volume index of industrial production, obtained from the Federal Reserve, and hours. We estimate the VAR with 24 lags, that is, we include two years as in the baseline model estimated on quarterly data.

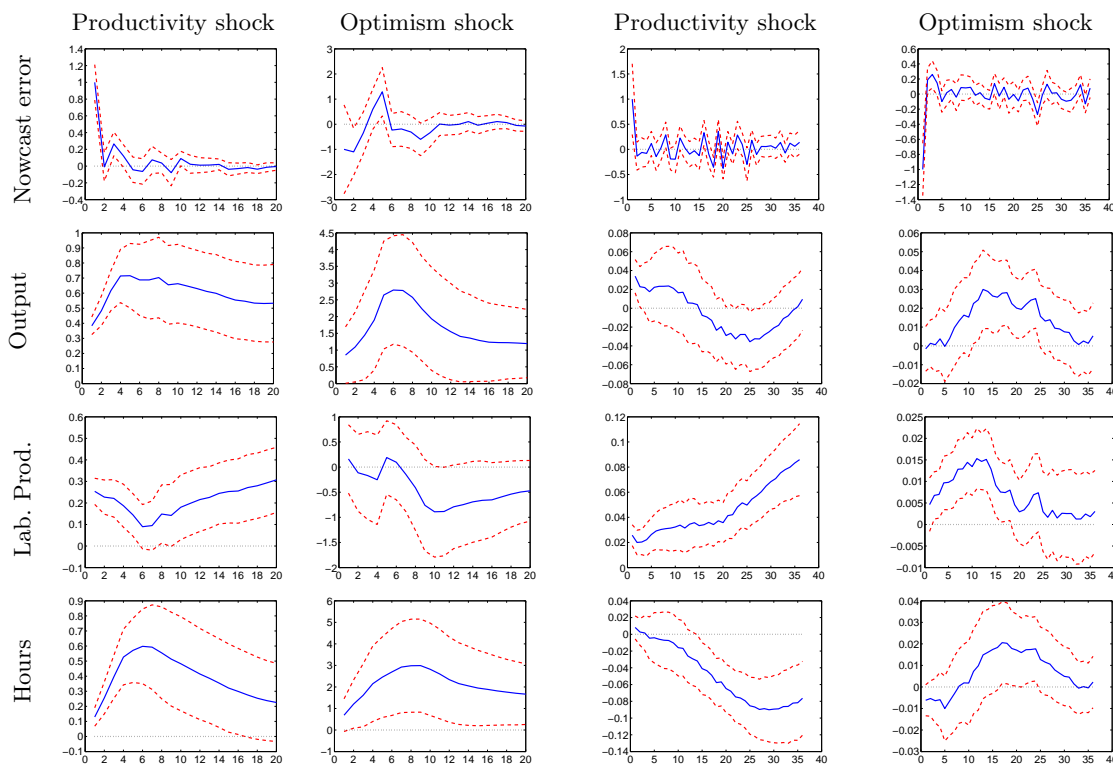


Figure 4: Impulse responses to productivity and optimism shock: Sensitivity analysis I. *Notes:* left panel shows results for nowcast error based on final-release data; right panel shows results for nowcast error based on monthly data for industrial production (sample: 1996M10–2012M12); horizontal axis measures months.

to those of the baseline specification (see Figure 2). An exception is the response of labor productivity to the productivity shock which turns insignificantly negative after about six quarters. However, in the long run (not shown), the response is positive as in the baseline VAR. The right panel of Figure 5 shows results for the model estimated on four lags only. Again, results are fairly similar to those obtained under the baseline specification. Finally, we explore the robustness of our results with respect to alternative assumptions regarding potential trends 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 productivity shock. This is not the case in our setup. Recall that we do not allow for a trend in hours in our baseline specification. Figure 6 shows results for a specification where hours enter in first differences (left panel) and for a specification where a linear-quadratic trend has been removed from hours worked prior to estimation (right panel).²³

²³Hours entering the VAR model either in levels, first differences or detrended with a linear-quadratic trend

Sample starts 1968

Four lags

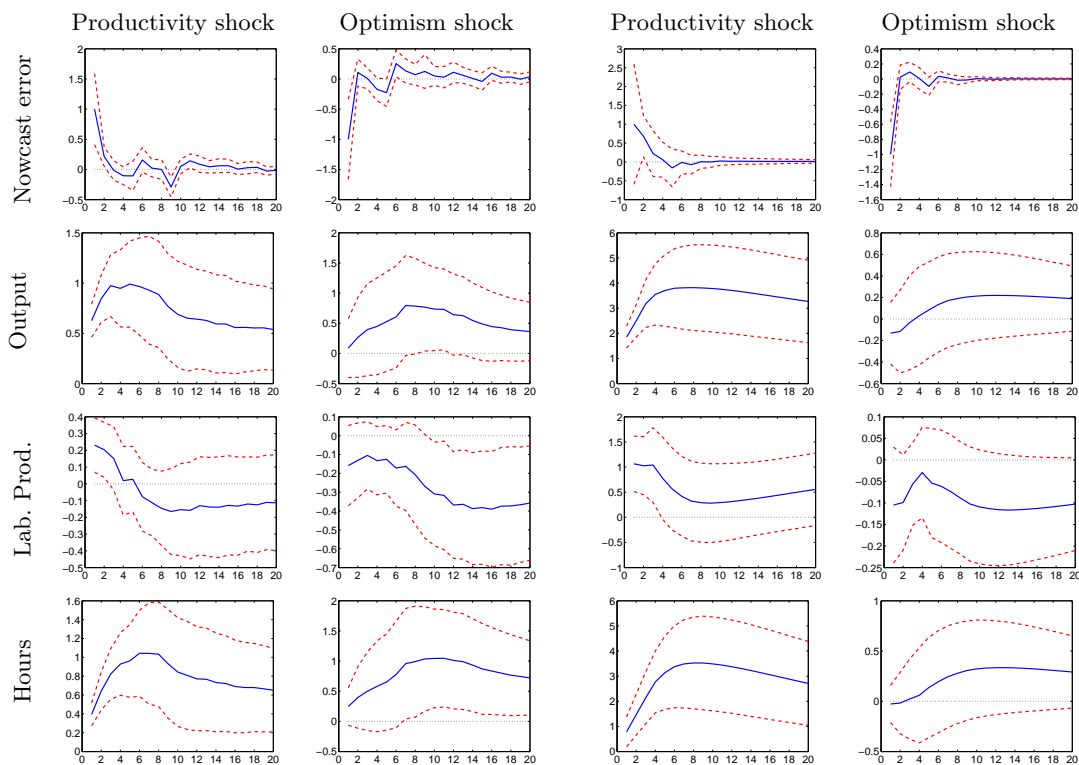


Figure 5: Impulse responses to productivity and optimism shock: Sensitivity analysis II. *Notes:* left panel shows results for baseline VAR model estimated on sample starting in 1968Q4, see Figure 2; right panel shows results for VAR model with four lags.

Our results may therefore also shed some light on the so-called “hours puzzle” (see Galí 1999, Francis and Ramey 2005, and Chari et al. 2008, among others). Given that hours unambiguously rise after (unexpected) productivity shocks under our identification scheme, a decline in hours documented elsewhere is likely due to productivity innovations which have no effect on nowcast errors. This, in turn, may be the result of innovations to productivity that have been anticipated.

5 Conclusion

To what extent are changes of expectations an autonomous source of business cycle fluctuations? In this paper, we pursue a new approach to address this question. Barsky and Sims (2012) and Blanchard et al. (2012) estimate fully-specified DSGE models to quantify the importance of “noise” or “undue optimism”, reaching quite different conclusions. We employ a

are commonly considered to be the most plausible specifications, see Galí and Rabanal (2005). Our results are also robust to detrending hours with a one-sided HP-filter.

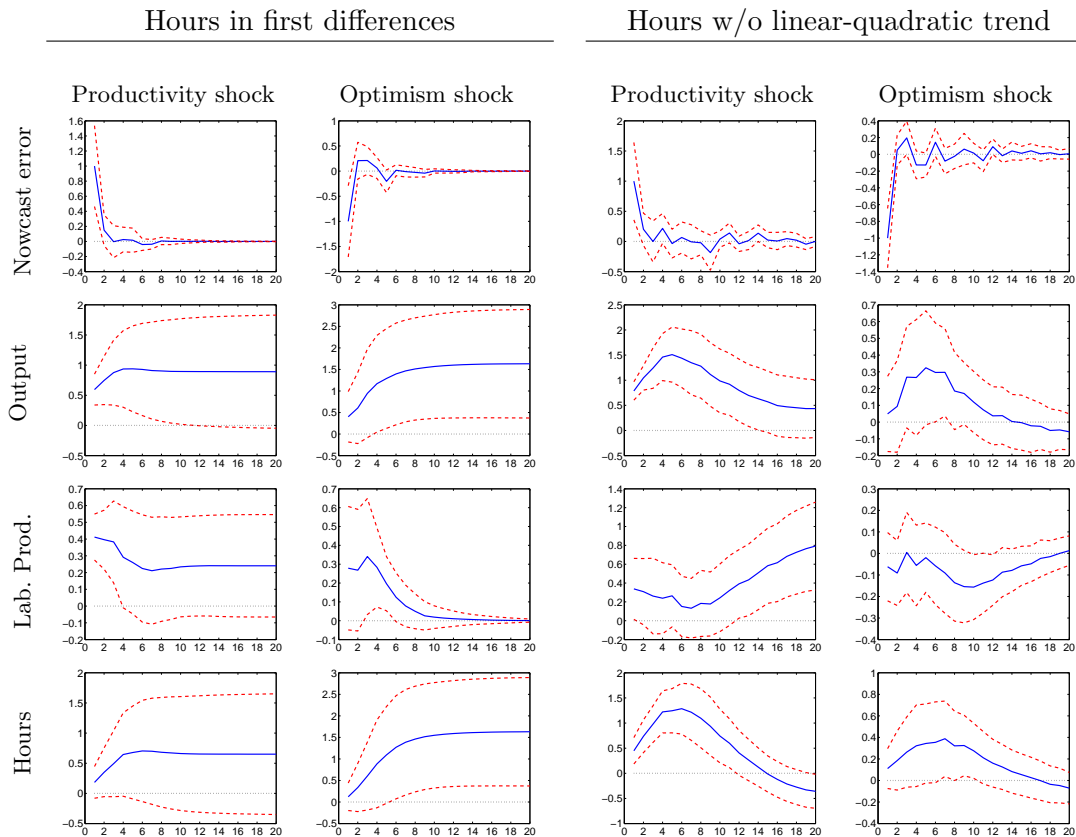


Figure 6: Impulse responses to productivity and optimism shock: Sensitivity analysis III. *Notes:* left panel shows results for hours in first differences, right panel for hours after a linear quadratic trend has been removed.

structural VAR model instead, thereby imposing less structure on the data. Yet, as shown by Blanchard et al. (2012), identifying the effects of optimism shocks within VARs 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 forecast in 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 find them not to be significantly affected by policy innovations or uncertainty shocks which are, in some sense, observable.

Drawing on Lorenzoni (2009), we put forward a stylized business cycle model which gives rise to nowcast errors due to productivity and optimism shocks, as agents do not observe output contemporaneously. Shocks which are common information do not generate a nowcast error. Importantly, we use this model to show that optimism shocks can be recovered from

time-series data on nowcast errors.

Given these results, we estimate a VAR model on U.S. time series including the nowcast error, labor productivity, and hours worked for the period 1980Q1–2012Q4. We identify unanticipated shocks to total factor productivity and optimism shocks by combining short and long-run restrictions. Specifically, we assume that optimism shocks and productivity shocks can trigger nowcast errors, but that optimism shocks do not affect labor productivity in the long run. We find that both shocks have a sizable and persistent effect on output, yet their effect on the nowcast error differs fundamentally. We find that productivity shocks induce a positive nowcast error, that is, growth is higher than expected. Optimism shocks, on the other hand, induce a negative nowcast error, that is, growth is lower than expected. While this result is quite intuitive, it is remarkable because it implies that the correlation of nowcast errors and economic activity conditional on optimism shocks changes sign relative to the unconditional correlation.

According to the forecast error variance decomposition, the contribution of optimism shocks rises to some 30 percent of output fluctuations at a 3-year horizon and declines thereafter. In the very short run our result is close to 20 percent, the value reported by Blanchard et al. (2012) for a 1-year horizon. Differences relative to Barsky and Sims (2012) are likely to reflect differences in the informational content of the nowcast error of current output growth on the one hand and of consumer sentiment data on the other.

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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 log-linear approximation to the equilibrium conditions of the model. Small-scale 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 decision 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 decisions, 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:

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

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

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

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 consumption. Using additionally $E_{l,t}p_{t+1} = E_{l,t}p_t$ and $E_{l,t}x_{t+1} = E_{l,t}x_t$ gives

$$c_{l,t} = E_{l,t}x_t + E_{l,t}p_t - p_{l,t} - r_t. \quad (\text{A.2})$$

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

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

Combining the above this gives

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

where $\rho_x^h = \rho_x^h + \rho_p^h$ 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. Below, 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, it 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

$$k' = \frac{\alpha}{\alpha + \gamma(1 - \alpha)} w_t \quad k'_1 = \frac{\gamma(1 - \alpha)}{\alpha + \gamma(1 - \alpha)} \quad k'_2 = \frac{1 - \alpha}{\alpha + \gamma(1 - \alpha)} \quad k'_3 = \frac{1}{\alpha + \gamma(1 - \alpha)}. \quad (\text{A.5})$$

Evaluating the expectation of firm j about aggregate output in period t , using 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 $\kappa^h = (1 + \tau_p^h)x_{t-1} - (1 + \eta_p^h)r_t + \kappa_p^h w_t$ is publicly available information. Furthermore, it is taken into account that 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 this in the above pricing equation yields (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

$$\Xi = 1 - \frac{1}{n}(k'_1 - k'_2) \quad k = \frac{1}{\Xi} \left\{ k' + k'_2 \kappa^h + \frac{k'_2 \delta_{xp}^h}{n} [(n-1)(1 - \delta_x^p) - 1] x_{t-1} \right\} \quad (\text{A.6})$$

$$k_1 = \frac{n-1}{n\Xi} (k'_1 - k'_2) \quad \tilde{k} = \frac{k'_2}{\Xi} \left(\rho_{xp}^h + \delta_{xp}^h \rho_x^p \frac{n-1}{n} \right) \quad k_3 = \frac{1}{\Xi} \left\{ k'_3 + \frac{k'_2 \delta_{xp}^h}{n} [(n-1)\delta_x^p - 1] \right\}.$$

Aggregating over all producers gives the aggregate price index

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

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

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

Inserting the last equation into (A.6) gives

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

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

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

where $\bar{E}^{(2)}$ 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:

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

Continuing like this results in some infinite sums

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

For the terms in the third line (see below for the proof that $|k_1| < 1$) we have

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

Proceeding similarly with the terms in the second line results in

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

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

$$p_t \equiv \bar{k}_1 + \bar{k}_2 s_t + \bar{k}_3 x_t,$$

with

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

To arrive at qualitative predictions for output growth and the nowcast error after the structural shocks ε_t and e_t , we need to determine the sign and the size of \bar{k}_3 . Note that according to (A.5), $0 < k'_1 - k'_2 < 1$ because $0 < \alpha < 1$ and $\gamma > 1$. According to the definition of k_1 in (A.6), this implies (observe that $n > 1$)

$$0 < k_1 < 1.$$

Turning to k_3 , note that, according to (A.6)

$$-k_3 = \delta_{xp}^h \frac{k'_2 - n k'_3 / \delta_{xp}^h + k'_2 (n - 1) \delta_x^p}{n - (k'_1 - k'_2)}.$$

The first nominator in the bracket is, observing (A.5),

$$k'_2 - n k'_3 / \delta_{xp}^h = \frac{1 - n / \delta_{xp}^h - \alpha}{\alpha + \gamma(1 - \alpha)}.$$

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

$$-k_3 = \delta_{xp}^h \frac{(1-\alpha)[(n-1)\delta_x^p + 1] - n/\delta_{xp}^h}{(n-1)[\alpha + \gamma(1-\alpha)] + 1}.$$

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

$$\bar{k}_3 = \delta_{xp}^h \frac{\frac{(1-\alpha)[(n-1)\delta_x^p + 1] - n/\delta_{xp}^h}{(n-1)[\alpha + \gamma(1-\alpha)] + 1}}{1 - \delta_x^p \frac{(n-1)(\gamma-1)(1-\alpha)}{(n-1)[\alpha + \gamma(1-\alpha)] + 1}}.$$

To obtain $\delta_{xp}^h = \delta_x^h + \delta_p^h$, 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):

$$E_{l,t} p_t = \underbrace{\bar{k}_1 + \bar{k}_3 x_{t-1}}_{\kappa_p^h w_t + \tau_p^h x_{t-1} - \eta_p^h r_t} + \underbrace{(\bar{k}_2 + \bar{k}_3 \rho_x^h)}_{\rho_p^h} s_t + \underbrace{\bar{k}_3 \delta_x^h}_{\delta_p^h} \hat{a}_{l,t}. \quad (\text{A.9})$$

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

$$\bar{k}_3 \equiv - \frac{n/\Upsilon - \delta_x^h \Psi}{\Phi - \delta_x^h \Psi}, \quad (\text{A.10})$$

with

$$\begin{aligned} \Upsilon &= (n-1)[\alpha + \gamma(1-\alpha)] + 1 > 0 & \Psi &= (1-\alpha)[(n-1)\delta_x^p + 1]/\Upsilon > 0 \\ \Phi &= 1 - \delta_x^p (n-1)(\gamma-1)(1-\alpha)/\Upsilon. \end{aligned}$$

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,

$$\begin{aligned} n/\Upsilon - \delta_x^h \Psi &> 0 \\ n - \underbrace{\delta_x^h}_{>0, <1} \underbrace{\Psi\Upsilon}_{<n} &> 0, \end{aligned}$$

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

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

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 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 realizes 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

$$E_t \pi_t = 0,$$

used in the derivations above. Nominal wages are set in line with these expectations. We thus have determinacy of the price level. The central bank, setting the interest rate after wages are determined, 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)

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

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

$$\begin{aligned} \bar{k}_1 = & \frac{1}{(1 - k_1)\Xi} \left[\frac{\alpha}{\alpha + \gamma(1 - \alpha)} + k_2' \kappa_p^h \right] w_t - \frac{k_2'(1 + \eta_p^h)}{(1 - k_1)\Xi} r_t \\ & + \frac{1}{(1 - k_1)\Xi} \left\{ k_2'(1 + \tau_p^h) + k_2' \delta_{xp}^h \left[\frac{n-1}{n} (1 - \delta_x^p) - 1 \right] - \frac{(1 - \delta_x^p) k_1 k_3 \Xi}{1 - k_1 \delta_x^p} \right\} x_{t-1}. \end{aligned}$$

Hence,

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

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

$$r_t = \psi \frac{\alpha - 1}{\alpha} r_t + \theta_t = \frac{\alpha}{\alpha + \psi(1 - \alpha)} \theta_t. \quad (\text{A.11})$$

B Proofs

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

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

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

$$y_t = x_{t-1} + \rho_x^h(1 - \Omega)e_t + \left[(\delta_x^h + \rho_x^h)(1 - \Omega) + \Omega \right] \varepsilon_t - \frac{\alpha}{\alpha + \psi(1 - \alpha)} \theta_t. \quad (\text{B.12})$$

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

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 .

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

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

or

$$y_t - E_{k,t}y_t = -\rho_x^k \left[\delta_x^h(1 - \Omega) + \Omega \right] e_t + \left[\delta_x^h(1 - \Omega) + \Omega \right] (1 - \delta_x^k - \rho_x^k) \varepsilon_t. \quad (\text{B.13})$$

The fact that $0 < \Omega < 1$ (see Appendix A) allows us to determine the signs of the effects of the shocks on the nowcast error. \blacksquare

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

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

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

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) representation²⁴

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

²⁴Note 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. ■

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

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

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