Does demand noise matter?
Identification and implications

Online Appendix

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Contents

1 The New Keynesian Model

Here we give the details of the model summarized in Section 4 of the main text. There is a continuum $[0,1]$ of households who work and consume a final good, a continuum $[0,1]$ of islands, each inhabited by a continuum $[0,1]$ of oligopolistic firms producing differentiated intermediate goods using labor and by a competitive firm using the differentiated goods to produce a final good. Nominal prices are set following Calvo pricing: at the beginning of each period, firms of the intermediate goods sector get the opportunity to reset their price with probability $1-\theta$. A central bank sets the nominal interest rate following a Taylor rule. Firms are hit by technology shocks that shift the productivity of labor while households are hit by preference shocks that shift their factor of time preferences.

We model survey expectations by introducing a continuum $[0,1]$ of surveyors who produce nowcasts. They are key in our setup since they allow to distinguish the "survey" expectations from the "agents" expectations. Agents expectations are the expectations of the agents of the economy that are relevant for their decision-making. Survey expectations are relevant empirically as they will enable us to relate expectation errors to the shocks.

1.1 Preferences, Technology and Policy

Timing and trading A period is divided in four stages, as described in Figure A1. In stage 1, households trade contingent claims in a centralized market. These claims are paid in the next period's first stage. The market for contingent claims closes in the next two stages. In stage 2, shocks are realized and all agents receive private and public signals. Firms set their prices, the central bank sets the interest rate, households decide consumption and surveyors produce nowcasts. In stage 3, local good markets open on each island. Namely, nature randomly selects an island $l(i,t) \in [0,1]$ visited by household i to shop. Similarly, firms of island i are visited by a household $k(i,t) \in [0,1]$ to shop. Households also visit a centralized labor market to supply labor. The centralized labor market clears and the production of differentiated and final goods takes place. Finally, in stage 4, contingent claims are settled and the households receive firms' profits from all production islands.

Preferences and technology Household i's utility is given by

$$U_{it} = E_t \sum_{s=0}^{\infty} B_{t+s} \left\{ \log(C_{it+s}) - \frac{1}{1+\zeta}(N^i_{t+s})^{1+\zeta} \right\}, \tag{A1}$$

where B_t is the coefficient of time preference for date t defined by $B_t = \beta B_{t-1} e^{-u^b_{t-1}}$ with $B_0 = 1$. C_{it} is the consumption of the final good and N^i_t is the quantity of labor supplied by i. β is the average factor of time preference and u^b_t is an intertemporal time preference shifter following the process:

$$u^b_t = \rho_b u^b_{t-1} + \epsilon^b_t, \tag{A2}$$

with $\epsilon^b \sim \mathcal{N}(0, \sigma^2_b)$. Household i decides both consumption C_{it} for period t, and the labor supply N_{it} by maximizing A1.

In each production island i, a competitive final good firm combines a continuum of differentiated intermediate goods produced on i in quantities Y_{ijt}, with $j \in [0,1]$ to produce the final good Y_{it}, following the typical production function

$$Y_{it} = \left(\int_0^1 Y_{ijt}^{(\gamma-1)/\gamma} dj \right)^{\gamma/(\gamma-1)}, \tag{A3}$$

where γ is the input demand elasticity, with $\gamma > 1$. The final good is then sold at price P_{it} on island i.

On production island i, each type-j intermediate good is produced by firm j and sold at price P_{ijt}. Firm j produces using a quantity of labor N_{ijt} with the production function

$$Y_{ijt} = A_t N_{ijt}, \tag{A4}$$

where A_t is a productivity shifter. Let $A_t = \bar{A} e^{u^a_t}$ where u^a_t follows a random walk:

$$u^a_t = u^a_{t-1} + \epsilon^a_t, \tag{A5}$$

with $\epsilon^a_t \sim \mathcal{N}(0, \sigma^2_a)$. Notice that technology shocks have a permanent component while preference shocks are transitory, see Equations (A2) and (A5). Nominal rigidities in price-setting follow Calvo (1983): each period, a fraction $1 - \theta$ of firms in the intermediate good sector are able to re-optimize their prices on each island.

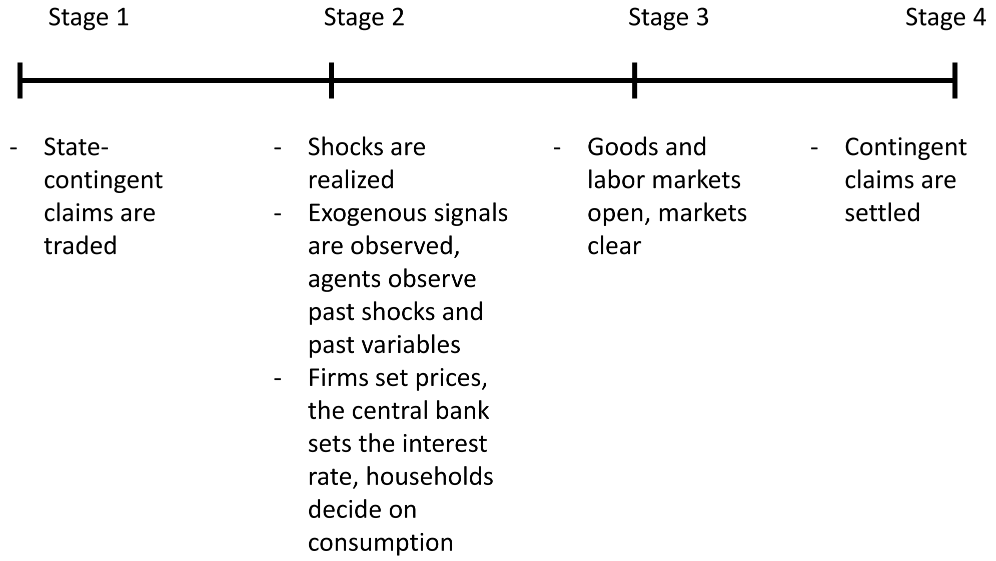
Monetary policy The central bank forms expectations on inflation and sets the interest rate on one-period-maturity nominal deposits according to the rule

$$i_t = \bar{\imath} + \varphi E^g_t(\pi_t), \tag{A6}$$

where $\pi_t = p_t - p_{t-1}$ with $p_t = \log(P_t)$ the average price across islands ($P_t = \int_0^1 P_{it} di$), and $E^g_t(.)$ is the expectation of the central bank.

Households own equal shares in the firms. The representative household faces then the

Figure A1: Timeline



following budget constraint:

$$(1+i_t)D_{it+1}+\int_0^1 P_{jt}C_{ijt}dj+\int Q(\omega_{it})Z_{it+1}(\omega_{it})d\omega_{it} = D_{it}+W_tN_t^i+\int_0^1\left(\int_0^1 P_{jt}Y_{jt}dj\right)di+Z_{it}(\omega_{it-1}), \tag{A7}$$

where D_{it+1} denotes the nominal deposits, W_t is the nominal wage. ω_{it} denotes the state, which depends on the set of aggregate and idiosyncratic shocks that occur in the second stage. $Q(\omega_{it})$ is the unit price of a contingent claim that delivers 1 in state ω_{it}. $Z_{it+1}(\omega_{it})$ are the quantities of contingent claims bought by the household.

Each household starts with zero deposits so $D_{it} = 0$. Since households face idiosyncratic shocks, their ex post deposits may evolve over time. However, since they have access to state-contingent claims and since they face identical shocks ex ante, they can fully insure against those shocks. Since in equilibrium we have $\int_0^1 D_{it}di = 0$, their ex post net position therefore stays equal to zero over time. This eliminates ex post heterogeneity across households, which greatly simplifies the problem.

1.2 Agents' Information

The information structure follows Woodford (2003). Agents either observe the shocks directly, or they learn exclusively from public and private signals on the shocks. To avoid the "infinite regress" issue that pertain to models with higher-order beliefs, we assume that all agents learn past shocks after T periods. More precisely, at stage 2 of date t, firms learn their productivity u_t^a and the households learn the households' preferences u_t^b. Additionally, the households, the firms, the surveyors and the central bank all receive exogenous public signals about the fundamentals u_t^a and u_t^b and learn u_{t-T}^a and u_{t-T}^b.[1]

We denote by s_t^n, $n = a, b$, the public signal received by all the agents at date t regarding shock ϵ_t^n, so that we have, for $n = a, b$:

$$s_t^n = u_t^n + e_t^n, \tag{A8}$$

where $e_t^n \sim \mathcal{N}(0, \sigma_{0n}^2)$. e_t^a and e_t^b correspond respectively to the productivity and preference noise shocks while ϵ_t^a and ϵ_t^b are the corresponding fundamental shocks.

Besides, household $i \in [0,1]$ receives the following private signal about productivity:

$$x_{it}^{ac} = u_t^a + \lambda_{it}^{ac}, \tag{A9}$$

where $\lambda_{it}^{ac} \sim \mathcal{N}(0, (\sigma_{1a}^c)^2)$ satisfies $\int_0^1 \lambda_{it}^{ac} di = 0$.

Similarly, firms on island $i \in [0,1]$ receive the following private signal about preferences:

$$x_{it}^{bf} = u_t^b + \lambda_{it}^{bf}, \tag{A10}$$

where $\lambda_{it}^{bf} \sim \mathcal{N}(0, (\sigma_{1b}^f)^2)$ satisfies $\int_0^1 \lambda_{it}^{bf} di = 0$.

Surveyors receive private signals on both technology and preferences:

$$x_{it}^{ns} = u_t^n + \lambda_{it}^{ns}, \tag{A11}$$

for $n = a, b$, where $\lambda_{it}^{ns} \sim \mathcal{N}(0, (\sigma_{1n}^s)^2)$ satisfies $\int_0^1 \lambda_{it}^{ns} di = 0$.

Finally, when setting the interest rate in stage 2, the central bank observes the public signals but does not have access to a private source of information. Thus, despite being observed by households, the interest rate is not informative. This assumption reflects the idea that the central bank communication is transparent: upon setting its interest rate, the central bank communicates whatever private information it has, so the central bank information becomes public. It is subsumed in the public signals s_t^a and s_t^b.

Agents expectations are defined as follows: $E_{it}^m(.) = E(.|I_{it}^m)$, $m = f, c, s$, where f, c and s denote respectively firms, households, and surveyors at stage 2, and I_{it}^m is the information set of agent m. $E_t^g(.) = E(.|I_t^g)$ is the expectation of the central bank when setting the interest rate at stage 2.

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[1] Assuming for simplicity an exogenous information structure is common. Beyond Woodford (2002), see for instance Angeletos and La'o (2009), Nimark (2014), Melosi (2014), or Angeletos et al. (2014).

Market timing assumptions are important. Firms set prices, household decide consumption of the final good and the central bank sets the nominal interest rate in stage 2, before the goods, bond and labor markets open in stage 3. Prices, consumption and the nominal interest rate are therefore predetermined within the period and are then conditional on private and public signals. In particular, firms do not observe the marginal cost before they set their prices.[2] Labor decisions, by contrast, are taken conditional on the nominal wage observed on the island, in the fourth stage. Since the households at this stage know their consumption, nominal price, nominal wage and labor supply, the nominal wage (and hence the marginal cost) will perfectly reflect the nominal marginal rate of substitution of the working household.

Importantly, we assume that, despite prices (wage, goods prices, interest rate) clear markets, agents do not use them to form expectations. While unrealistic, this assumption is useful to derive closed-form solutions, as information sets do not depend on endogenous variables. Besides, it makes our numerical computations easier and our results more transparent. The agents' information sets are then exogenous and are defined precisely in the following assumption:

Assumption 1 (Exogenous information) *Define the information set common to the whole economy as* $I_t = \left\{ \left(s^n_{t-s}\right)_{0\leq s<T, n=a,b}, \left(u^n_{t-T}\right)_{n=a,b}, P_{t-T}, \left(P_{iT-1}\right)_{i\in[0,1]} \right\}$. *We have* $I^g_t = I_t$, $I^f_{it} = \left\{ \epsilon^a_t, \left(x^{bf}_{it-s}\right)_{0\leq s<T}, I_t \right\}$, $I^c_{it} = \left\{ \epsilon^b_t, \left(x^{ac}_{it-s}\right)_{0\leq s<T}, I_t \right\}$, *and* $I^s_{it} = \left\{ \left(x^{ns}_{it-s}\right)_{0\leq s<T, n=a,b}, I_t \right\}$.[3,4]

1.3 Summary of the Model

Except for the information structure, this model is close to Galì (2008). Small-case letters denote variables in log-deviation from their steady-state value. From the households perspective, the Euler equation on consumption and bonds yields:

$$c_{it} = E^c_{it}\left\{c_{it+1}\right\} - \left(i_t - E^c_{it}\left\{\pi_{it+1}\right\}\right) + u^b_t. \tag{A12}$$

where $\pi_{it+1} = p_{l(i,t+1)t+1} - p_{l(i,t)t}$. The Euler equation depends the expected real interest rate $i_t - E^c_{it}\left\{\pi_{it+1}\right\}$, on the expectation about future consumption and on the preference disturbance.

A firm j that is part of the portion $1-\theta$ of firms who reset their price in period t on island i sets the following price that depends on the expected marginal cost in the period and on the future optimal price (see the proofs for details):

$$p^*_{ijt} = p^*_{it} = (1-\beta\theta)[E^f_{it}(w_t) - u^a_t] + \beta\theta E^f_{it}(p^*_{it+1}) \tag{A13}$$

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[2] This assumption is a natural one. First, in the New Keynesian literature, prices are typically predetermined. Second, marginal costs are notoriously difficult to measure.

[3] We do not keep track of past values of u^n_t and x^n_{it} beyond u^n_{t-1} and x^n_{it-1}, $n = a, b$. This is because agents learn the past value u^n_{t-1}, which is enough to summarize the current state of the economy. Keeping track of past shocks would not be relevant in that case.

[4] In our setup, there is asymmetric information between firms and households, and among firms and households as well, which generates higher-order beliefs. The assumption that agents learn past variables reduces the dimensionality issue that is typical of higher-order beliefs. See Woodford (2003), Nimark (2008) and Melosi (2014).

where w_t is determined as follows:

$$w_t - p_t = c_t + \zeta n_t. \tag{A14}$$

where we used the labor supply of household i, $w_t - p_{l(i,t)t} = c_{it} + \zeta n_t^i$, aggregated across households. We used $\int_0^1 p_{l(i,t)t} di = \int_0^1 p_{it} di = p_t$, where p_{it} is the log of the price of the final good on island i, $\int_0^1 c_{it} di = c_t$ and $\int_0^1 n_t^i di = n_t$.

The price of the final good on island i is $P_{it} = \left(\int_0^1 (P_{ijt})^{1-\gamma} di\right)^{\frac{1}{1-\gamma}}$. The log-linearization of this equation gives us $p_{it} = \int_0^1 p_{ijt} dj$. Since firms are identical, p_{ijt} depends only on the last date where j has reset its price, following A13. We can then show that p_{it} on island i is defined by

$$p_{it} = \theta p_{it-1} + (1-\theta) p_{it}^* \tag{A15}$$

Additionally, the production functions and the resource constraints in island i respectively read $n_{it} = y_{it} - u_t^a$ and $y_{it} = c_{k(i,t)t}$, which yields on the aggregate:

$$n_t = y_t - u_t^a. \tag{A16}$$

$$y_t = c_t. \tag{A17}$$

where we used $\int_0^1 c_{it} di = c_t$, $\int_0^1 y_{it} di = y_t$ and $\int_0^1 n_{it} di = n_t$. Finally, the central bank follows the simple rule A6.

Equilibrium definition For given functions k and l, given past values p_{t-T}, p_{it-T}, $i \in [0,1]$, u_{t-T}^a and u_{t-T}^b, given aggregate shocks $\{\epsilon_{t-s}^n, e_{t-s}^n\}_{0 \leq s < T, n=a,b}$ and idiosyncratic shocks $\left\{ \left\{\lambda_{it-s}^{ac}\right\}_{i\in[0,1]}, \left\{\lambda_{it-s}^{bf}\right\}_{i\in[0,1]}, \left\{\lambda_{it-s}^{ns}\right\}_{i\in[0,1], n=a,b} \right\}_{0\leq s<T}$ and laws of motionA2 and A5, a period-t equilibrium is defined by aggregate quantities $\{c_t, y_t, n_t\}$, individual quantities $\{c_{it}, y_{it}, n_{it}\}_{i\in[0,1]}$, aggregate prices $\{p_t^*, p_t, w_t, i_t\}$ and individual prices $\{p_{it}^*, p_{it}\}_{i\in[0,1]}$ satisfying Equations A6 and A12-A17, $\int_0^1 y_{it} di = y_t$, $\int_0^1 c_{it} di = c_t$, $\int_0^1 p_{it} di = p_t$, $\int_0^1 n_{it} di = n_t$ and where expectations are conditional on the information sets defined in Assumptions 1.

A limit case We derive the model's prediction in our benchmark specification, with i.i.d. demand shocks: $\rho_b = 0$ and when agents learn last period's shocks ($T = 1$). These two assumptions enable us to derive closed-form results.

1.4 Model's Predictions in the Limit Case

Note that, since $\rho_b = 0$, $s_t^b = \epsilon_t^b + e_t$ and $x_{it}^{bf} = \epsilon_t^b + \lambda_{it}^{bf}$. Similarly, because agents learn u_{t-1}^a, observing $u_t^a + e_t^a$ ($u_t^a + \lambda_{it}^{ac}$) is equivalent to observe $\epsilon_t^a + e_t^a$ ($\epsilon_t^a + \lambda_{it}^{ac}$). We therefore redefine s_t^a and x_{it}^{ac} as $s_t^a = \epsilon_t^a + e_t^a$ and $x_{it}^{ac} = \epsilon_t^a + \lambda_{it}^{ac}$, without loss of generality.

1.4.1 Output and Inflation

In the benchmark case, Assumption 1 holds. Denote by $\bar{E}_t^m(.) = \int_0^1 E_{it}^m(.)di$, $m = c, f, s$, the aggregate expectations.

Consider the Euler equation A12. Aggregating across households and using (A6) and (A17), we obtain (see Section 1.5 for details):

$$y_t = \bar{E}_t^c \left\{ y_{t+1} + \pi_{t+1} \right\} - \varphi E_t^g \left\{ \pi_t \right\} + u_t^b. \tag{A18}$$

Equation A18 corresponds to the aggregate Euler equation, or the New IS. Unlike the traditional New IS, it does not depend on a homogenous expectation of future output and inflation, but on the average of households' expectations.

Using Equations A13-A17 and aggregating across firms and islands, we obtain the aggregate Phillips curve (see Section 1.5 for details):

$$\begin{aligned} \pi_t \quad = \quad & \kappa \left(\bar{E}_t^f \left\{ y_t \right\} - u_t^a \right) + \beta \bar{E}_t^f \left\{ \pi_{t+1} \right\} \\ & + \tfrac{1-\theta}{\theta} \left[\bar{E}_t^f \left\{ \pi_t \right\} - \pi_t \right] \\ & + (1-\theta) \beta \bar{E}_t^f \left\{ p_{it+1}^* - p_{t+1}^* \right\}. \end{aligned} \tag{A19}$$

where $\kappa = (1+\zeta)(1-\theta)(1-\beta\theta)/\theta$. The first two terms can be related to the New Keynesian Phillips curve. The first term depends on the average firms' *expected* output gap and the second term depends on the average expectations by firms of future inflation. Dispersed information introduces some additional terms. The third term depends on the difference between the average inflation expectations and actual inflation. It reflects higher-order beliefs that typically arise in the presence of dispersed information: if firms expect that other firms set higher prices, strategic complementarities in price-setting leads them to set higher prices. The fourth term simply represents the fact that firms are concerned about their individual future optimal price when setting their current price, and not the aggregate one.

Consider now u_t^a and u^b. They appear here respectively as a supply shifter (it corresponds to capacity output) and a demand shifter. While supply u_t^a shifts Equation A19, the aggregate Phillips curve, demand u_t^b shifts the aggregate Euler equation A18.

Notice that the demand shifter, everything else equal, has a positive effect on current output. Notably, a shift in households' expectations on future output has a similar effect. This is consistent with Lorenzoni (2009), who shows that supply-noise shocks (i.e. overly optimistic expectations on future output) have an effect on the economy that is observationally equivalent to demand shocks. Similarly, the supply shifter has a negative effect on inflation, while a shift in firms' expectations on current aggregate demand has a positive effect. Consistently, we will show that positive demand-noise shocks (i.e. overly optimistic expectations on demand) have an effect that is observationally equivalent to negative supply shocks.

It is useful to define the following condition:

Condition 1 $\theta\kappa\varphi\sigma_{1b}^{-2} < \sigma_b^{-2} + \sigma_{0b}^{-2}$.

The effect of shocks on output and inflation is then summarized by the following proposition (see the proof in Section 1.5).

Proposition 1 (Responses of output and inflation) *With* $T = 1$ *and* $\rho_b = 0$*, we establish that, if* $\sigma_{0n}^{-2} > 0$*, for* $n = a, b$*:*

(i) *Fundamental supply shocks* ϵ_t^a *have a permanent, positive effect on output* y_t *and a negative effect on inflation* π_t*.*

(ii) *Supply-noise shocks* e_t^a *have a temporary, positive effect on output and a positive effect on inflation.*

(iii) *Fundamental demand shocks* ϵ_t^b*, have a temporary, positive effect on output and a positive effect on inflation.*

(iv) *Demand-noise shocks* e_t^b*, have a temporary, negative effect on output. They have a positive effect on inflation if and only if Condition 1 is satisfied.*

Result (i) is standard in New Keynesian models: a positive productivity shock has a permanent, positive effect on output and a negative effect on inflation. First, consumers increase their consumption because they receive a positive signal about productivity, which is permanent. Firms decrease their prices as a response to a lower marginal cost. The negative response of the policy rate to this deflation further stimulates demand.

Note that result (ii) is reminiscent of Lorenzoni (2009), that is supply-noise shocks behave as demand shocks. As in the case of a fundamental productivity shock, consumers increase their consumption because they receive a positive signal about productivity. Since this increase in demand is not matched by an actual increase in productivity, firms increase their prices in expectation of an increase in the marginal cost.

Result (iii), which states that fundamental demand shocks are both expansionary and inflationary, is also standard in New Keynesian models. Here, these shocks have a direct, positive effect on aggregate demand. As firms receive a positive signal about aggregate demand, they increase their prices in expectation of higher marginal costs.

Result (iv), which describes the effects of demand-noise shocks, is new. Namely, a positive noise shock provokes a decrease in output. The central bank increases the interest rate, as it anticipates a boost in demand and therefore a price increase. Consumers respond to this increase in interest rate by decreasing consumption, which generates a decrease in output. We will show below that this result is more ambiguous when firms also make quantity decisions.

The effect of demand-noise shocks on inflation is ambiguous and depends on Condition 1. When firms receive a positive public signal about the demand shock, they anticipate a positive demand shock, but they also anticipate an interest rate increase, which has a negative effect on aggregate demand. The effect on inflation is then positive if firms anticipate an overall rise in aggregate demand. This happens if the slope of the Phillips curve times the response of the policy rate to inflation $\kappa\varphi$ is small and if the firms do not have too much of an advantage in detecting the noise shock as compared to the central bank, hence if the private signals received by firms are not too precise as compared to the public signal, shared by both firms and the central bank.

The role of information Intuitively, to generate an effect of aggregate noise shocks on output and inflation, only public signals are needed. This can be seen by setting σ_{1a}^{-2} and σ_{1b}^{-2}, the precisions of the private signals, to zero. In that case, Proposition 1 still holds, as it requires only $\sigma_{0a}^{-2} > 0$ and $\sigma_{0b}^{-2} > 0$. However, as we will see, private signals play a key role to generate expectation errors on behalf of surveyors.

The Role of Monetary Policy Monetary policy is a central channel to understand the effect of noise shocks on the economy. In the case of a supply-noise shock, the central bank, because it expects a deflation, decreases the interest rate, which accentuates the positive response of aggregate demand. What drives the recession after a demand-noise shock is the increase in interest rate due to the expected inflation by the central bank.

1.4.2 Expectation Errors

We now examine the model's predictions in terms of expectation errors of professional surveyors and analyze the conditions under which our predictions hold and expectation errors can be used to identify the shocks.

1.4.3 Predictions on Expectation Errors

The effect of shocks on expectation errors is summarized in the following proposition (see the proof in Section 1.5).

Proposition 2 (Responses of errors in survey expectations) *With* $T = 1$ *and* $\rho_b = 0$, *we establish that, if* $\sigma_{0n}^{-2} > 0$, *for* $n = a, b$, $(\sigma_{1a}^{c})^{-2} > 0$ *and* $(\sigma_{1b}^{f})^{-2} > 0$*:*

(i) *Fundamental supply shocks* ϵ_t^a *(supply-noise shocks* e_t^a*) have a negative (positive) effect on the average survey expectation error on output* $\bar{E}_t^s y_t - y_t$ *and a positive (negative) effect on the average survey expectation error on inflation* $\bar{E}_t^s \pi_t - \pi_t$*.*

(ii) *Fundamental demand shocks* ϵ_t^b *(demand-noise shocks* e_t^b*), have a negative (positive) effect on both the average survey expectation error on output and the average survey expectation error on inflation.*

We find that fundamental shocks that induce a positive (negative) response of endogenous variables tend to generate a negative (positive) error on these variables by the surveyors. Corresponding noise shocks then generate a positive (negative) error. Said differently, the fundamental shock leads the surveyors to underestimate the actual response of the variable while the noise shock leads them to overestimate it. For instance, the supply-noise shock drives the

Table A1: New Keynesian Model: Sign restrictions

	y_t	π_t	$E_t^s(y_t) - y_t$	$E_t^s(\pi_t) - \pi_t$
Supply (ϵ_t^a)	+ (permanently)	-	-	+
Supply noise (e_t^a)	+	+	+	-
Demand (ϵ_t^b)	+	+	-	-
Demand noise (e_t^b)	-	+	+	+

Note: The signs are from Propositions 1 and 2.

surveyors to overestimate output, while the fundamental shock drives them to underestimate it. Besides, a positive demand-noise shock can be distinguished from a negative supply shock by looking at inflation: the former leads the surveyors to overestimate inflation, while the latter leads them to underestimate it.[5] Table A1 summarizes the sign restrictions in our benchmark specification implied by Propositions 1 and 2.

The role of information Importantly, expectation errors arise in this model because of decision makers' (firms and households) private information. Indeed, if their information were public, then there would be no expectation errors, as surveyors would share the same – though possibly noisy – information. This can be seen by considering the limit case with vanishing precision of private signals σ_{1a}^{-2} and σ_{1b}^{-2}, as in the following corollary (see the proof in Section 1.5):

Corollary 2.1 (Agents without private signals) *With $T = 1$ and $\rho_b = 0$, we establish that, if $\sigma_{0n}^{-2} > 0$ for $n = a, b$ and $(\sigma_{1a}^c)^{-2} = (\sigma_{1b}^f)^{-2} = 0$:*

(i) *Fundamental supply and supply-noise shocks ϵ_t^a and e_t^a have no effect on the average survey expectation error on output.*

(ii) *Fundamental demand and demand-noise shocks ϵ_t^b and e_t^b have no effect on the survey average expectation error on inflation.*

In the absence of private information, fundamental supply and supply-noise shocks would have no effect on the expectation errors on output, because consumers and surveyors would share the same information on supply. Similarly, fundamental demand and demand-noise shocks would have no effect on the expectation errors on inflation, because firms and surveyors would share the same information on demand. The fact that firms observe productivity and that households observe preferences constitute also private information, and is at the source of the

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[5] Indeed, a positive demand shock would lead to inflation, so the surveyors anticipate inflation if they get a positive signal about demand. Inflation however does not materialize fully if the signal was in fact driven by noise, which implies that they overestimate inflation. Similarly, a negative supply shock leads to inflation, which will tend to be underestimated by the surveyors.

effect of fundamental supply and supply-noise shocks on the expectation errors on inflation and of the effect of fundamental demand and demand-noise shocks on the expectation errors on output.

On the opposite, the precision of the surveyors' private information σ^s_{1n} does not matter for the results in Proposition 2. What is important instead is that surveyors share the same public signal as decision-makers, otherwise, it would not be possible to disentangle fundamental shocks from noise based on the response of errors. To understand, consider a noise and a fundamental shock that have the same effect on output and inflation. What enables us to distinguish the fundamental from the noise is that survey expectations under-react to the fundamental and over-react to the noise, because observing the public signal makes surveyors over-optimistic. But if the public signal is not observed by surveyors, then their expectations do not react to the noise at all, so that expectation errors move in the same direction as with the fundamental shock and thus they cannot help disentangle the two shocks. We establish the following corollary in the polar case where surveyors do not observe the public signals s^n_t, $n = a, b$ (see the proof in the Appendix):

Corollary 2.2 (Surveyors without public signals) *With $T = 1$ and $\rho_b = 0$, we establish that, if $I^s_{kt} = \left\{z^a_{kt}, z^b_{kt}, I_t \backslash \left\{s^a_t, s^b_t\right\}\right\}$:*

(i) The effect of supply-noise shocks e^a_t on output, inflation and their corresponding survey expectation errors is of the same sign as a fundamental demand shock ϵ^b_t.

(ii) The effect of demand-noise shocks e^b_t on output, inflation and their corresponding survey expectation errors is of the same sign as a negative fundamental supply shock ϵ^a_t.

1.5 Proofs

This sub-section describes the model's computations as well as the proof to Propositions 1 and 2 and Corrollary 2.1 and 2.2.

1.5.1 Firms' price-setting

Firms set prices and supply goods. They observe their individual price and the quantities they supply. They are allowed to reset their price only at random interval with probability $(1 - \theta)$. Let P^*_{ijt} denote the optimal price for firm j on island i that can adjust its price at time t. This firm maximizes over P_{ijt} the following objective

$$\mathrm{E}^f_{it}\left\{ \sum_{\tau=0}^{+\infty} \theta^\tau \beta^\tau \lambda_{it+\tau} \left(P_{ijt+\tau} Y_{ijt+\tau} - W_{t+\tau} N_{ijt+\tau}\right) \right\},$$

subject to $P_{ijt+\tau} = P_{ijt}$, technology A4 and individual demand $Y_{ijt} = \left(\frac{P_{ijt}}{P_{it}}\right)^{-\gamma} C_{k(i,t)t}$. The term between brackets corresponds to the period nominal profits, composed of nominal sales, minus the nominal wage bill. These profits are discounted by the probability θ^τ that price

P_{ijt} is still in place and by the stochastic discount factor for nominal profits $\beta^{\tau}\lambda_{it+\tau}$, where $\lambda_{it+\tau} = P_{it}C_{it}/P_{it+\tau}C_{it+\tau}$ is the multiplier of the budget constraint in $t+\tau$ in household i's Lagrangian.

Maximizing the objective and linearizing the result yields

$$p^*_{ijt} = p^*_{it} = (1-\beta\theta)\sum_{\tau=0}^{+\infty}(\beta\theta)^{\tau}E^f_{it}(w_{t+\tau} - u^a_{t+\tau})$$

which implies

$$p^*_{it} = (1-\beta\theta)E^f_{it}(w_t - u^a_t) + \beta\theta E^f_{it}(p^*_{it+1})$$

1.5.2 Derivation of the New Keynesian model with imperfect information (Equations A18 and A19)

Here we derive the aggregate Euler equation A18 and the aggregate Phillips curve A19, which are obtained under exogenous information as described by Assumption 1.

Consider first the Euler equation A12. We can write $p_{l(i,t)t} = p_t + \xi^1_{it}$ where ξ^1_{it} is a function of the idiosyncratic noise in island $l(i,t)$ at date t, and p_t is the average price. Under exogenous information, this noise is orthogonal to the information of household i in stage 2, so $E^c_{it}(p_{l(i,t)t}) = E^c_{it}(p_t)$ and $E^c_{it}(p_{l(i,t+1)t+1}) = E^c_{it}(p_{t+1})$, hence $E^c_{it}(\pi_{it+1}) = E^c_{it}(\pi_{t+1})$, where π_{t+1} is the average future inflation. Similarly, because of perfect risk-sharing between households, current idiosyncratic shocks do not affect future consumption, we can write $c_{it+1} = c_{t+1} + \xi^2_{it+1}$ where ξ^2_{it+1} is a function of the idiosyncratic noise in period $t+1$. This noise is orthogonal to the information of household i in period t, so $E^c_{it}(c_{it+1}) = E^c_{it}(c_{t+1})$.

Using A6, we then obtain

$$c_{it} = E^c_{it}\{c_{t+1}\} + E^c_{it}\{\pi_{t+1}\} - \varphi E^g_t\{\pi_t\} + u^b_t. \tag{A20}$$

Aggregating Equation A17 across islands, we obtain

$$y_t = \int_0^1 y_{it}di = \int_0^1 c_{l^s(i,t)t}di = \int_0^1 c_{it}di = c_t.$$

Then, aggregating the Euler equation and replacing $c_t = y_t$ and $c_{t+1} = y_{t+1}$, we get Equation A18.

Now consider the optimal price A13. The optimal price p^*_{it} depends on the expected nominal marginal cost $w_t - u^a_t$. When setting their price, firms know u^a_t by assumption, but not w_t. Plugging Equations (A16) and Equation (A17) into (A14), we can see that the nominal wage w_t is equal to $p_t + c_t + \zeta(c_t - u^a_t)$, so $E^f_{it}(w_t) = E^f_{it}[p_t + c_t + \zeta(c_t - u^a_t)]$. Therefore, A13 writes

$$p^*_{it} = (1-\beta\theta)E^f_{it}[p_t + (1+\zeta)(c_t - u^a_t)] + \beta\theta E^f_{it}(p^*_{it+1}) \tag{A21}$$

Replacing $c_t = y_t$ in the optimal price, and aggregating across islands, we get

$$p_t^* = \int_0^1 p_{it}^* di = (1-\beta\theta)\bar{E}_t^f \left[p_t + (1+\zeta)(y_t - u_t^a)\right] + \beta\theta\bar{E}_t^f(p_{it+1}^*) \tag{A22}$$

Similarly, aggregating prices across islands, we obtain, using A15,

$$p_t = \int_0^1 p_{it} di = \theta \int_0^1 p_{it-1} di + (1-\theta)\int_0^1 p_{it}^* di = \theta p_{t-1} + (1-\theta)p_t^* \tag{A23}$$

Using A22 and A23 and rearranging:

$$\begin{aligned}
p_t - \theta p_{t-1} &= (1-\theta)p_t^* \\
&= (1-\theta)\left[(1-\beta\theta)\bar{E}_t^f[p_t + (1+\zeta)(y_t - u_t^a)] + \beta\theta\bar{E}_t^f(p_{it+1}^*)\right] \\
&= (1-\theta)\left[(1-\beta\theta)[p_t + (1+\zeta)\bar{E}_t^f(y_t - u_t^a)] + \beta\theta\bar{E}_t^f(p_{t+1}^*)\right] \\
&\quad +(1-\theta)\left[(1-\beta\theta)[\bar{E}^f(p_t) - p_t] + \beta\theta\bar{E}_t^f(p_{it+1}^* - p_{t+1}^*)\right] \\
&= (1-\theta)(1-\beta\theta)[p_t + (1+\zeta)\bar{E}_t^f(y_t - u_t^a)] + \beta\theta\bar{E}_t^f(p_{t+1} - \theta p_t) \\
&\quad +(1-\theta)(1-\beta\theta)[\bar{E}^f(p_t) - p_t] + \beta\theta(1-\theta)\bar{E}_t^f(p_{it+1}^* - p_{t+1}^*) \\
&= (1-\theta)(1-\beta\theta)[p_t + (1+\zeta)\bar{E}_t^f(y_t - u_t^a)] + \beta\theta[\bar{E}_t^f(p_{t+1} - p_t) + (1-\theta)p_t] \\
&\quad +(1-\theta)[\bar{E}^f(p_t) - p_t] + \beta\theta(1-\theta)\bar{E}_t^f(p_{it+1}^* - p_{t+1}^*)
\end{aligned}$$

This yields

$$\begin{aligned}
p_t - p_{t-1} &= \tfrac{(1-\theta)(1-\beta\theta)(1+\zeta)}{\theta}\bar{E}_t^f(y_t - u_t^a)] + \beta\bar{E}_t^f(p_{t+1} - p_t) \\
&\quad +\tfrac{1-\theta}{\theta}[\bar{E}^f(p_t) - p_t] + \beta(1-\theta)\bar{E}_t^f(p_{it+1}^* - p_{t+1}^*)
\end{aligned}$$

Then use $\pi_t = p_t - p_{t-1}$ and $\bar{E}^f(p_t) - p_t = \bar{E}^f(\pi_t) - \pi_t$ (as p_{t-1} is common knowledge) to find

$$\begin{aligned}
\pi_t &= \tfrac{(1-\theta)(1-\beta\theta)(1+\zeta)}{\theta}\bar{E}_t^f(y_t - u_t^a)] + \beta\bar{E}_t^f(\pi_{t+1}) \\
&\quad +\tfrac{1-\theta}{\theta}[\bar{E}^f(\pi_t) - \pi_t] + \beta(1-\theta)\bar{E}_t^f(p_{it+1}^* - p_{t+1}^*)
\end{aligned} \tag{A24}$$

which yields A19.

1.5.3 Proof of Proposition 1

We first solve for the equilibrium output and inflation y_t and π_t. We derive the following Lemma:

Lemma 1 *Under Assumption 1 and $\rho_b = 0$, the equilibrium output and inflation are*

$$\begin{aligned} y_t &= u^a_{t-1} + \tfrac{\delta^c_{0a}+\kappa\varphi\delta^g_{0a}(1-\delta^c_{1a})}{1+\kappa\varphi} s^a_t + \delta^c_{1a}\epsilon^a_t \\ &\quad \tfrac{-\kappa\varphi(\delta^f_{0b}+\theta\delta^f_{1b}\delta^g_{0b})}{(1+\kappa\varphi)[1-(1-\theta)\delta^f_{1b}]} s^b_t + \epsilon^b_t \\ \pi_t &= \kappa\left[\tfrac{\delta^c_{0a}+\kappa\varphi\delta^g_{0a}(1-\delta^c_{1a})}{1+\kappa\varphi} s^a_t - (1-\delta^c_{1a})\epsilon^a_t\right] \\ &\quad + \tfrac{\kappa}{1-(1-\theta)\delta^f_{1b}} \left[\tfrac{\delta^f_{0b}-\theta\kappa\varphi\delta^f_{1b}\delta^g_{0b}}{1+\kappa\varphi} s^b_t + \theta\delta^f_{1b}\epsilon^b_t\right] \end{aligned} \tag{A25}$$

with $\delta^m_{0n} = (\sigma_{0n})^{-2}/[(\sigma_n)^{-2} + (\sigma_{0n})^{-2} + (\sigma^m_{1n})^{-2}]$, $\delta^m_{1n} = (\sigma^m_{1n})^{-2}/[(\sigma_n)^{-2} + (\sigma_{0n})^{-2} + (\sigma^m_{1n})^{-2}]$ and $\delta^g_{0n} = (\sigma_{0n})^{-2}/[(\sigma_n)^{-2} + (\sigma_{0n})^{-2}]$ for $n = a, b$ and $m = c, f$.

Proof. We make the following educated guess:

$$\begin{aligned} \bar{E}^c_t(y_{t+1}) &= a_{t-1} + \bar{E}^c_t(\epsilon^a_t) \\ \bar{E}^c_t(\pi_{t+1}) &= \bar{E}^f_t(\pi_{t+1}) = 0 \\ \bar{E}^f_t(p^*_{it+1}) &= \bar{E}^f_t(p^*_{t+1}) \end{aligned} \tag{A26}$$

with $\bar{E}^c_t(\epsilon^a_t) = \delta^c_{0a}s^a_t + \delta^c_{1a}x^a_{it}$. It follows from A19 that

$$\pi_t = \theta\kappa\left(\bar{E}^f_t\{y_t\} - u^a_t\right) + (1-\theta)\bar{E}^f_t\{\pi_t\} \tag{A27}$$

We then make the guess that $\pi_t = \gamma_{0a}s^a_t + \gamma_{1a}\epsilon^a_t + \gamma_{0b}s^b_t + \gamma_{1b}\epsilon^b_t$ for some $(\gamma_{0a}, \gamma_{1a}, \gamma_{0b}, \gamma_{1b})$. We then replace our guess A26 in the system A18-A27 to derive y_t and π_t as a function of shocks and signals. We finally check that our guess A26 is satisfied. The first two equations are straightforward. Using the optimal pricing equation A13, along with A14, A16 and A17, we can show that $E_{it}(p^*_{it+1}) = E_{it}[E_{it+1}(p_{t+1})] = E_{it}(p_{t+1}) = E_{it}(p_t)$. Besides, $E_{it}(p^*_{t+1}) = E_{it}[\bar{E}^f_{t+1}(p_{t+1})] = E_{it}[p_t + \bar{E}^f_{t+1}(\pi_{t+1})] = E_{it}(p_t) + E_{it}[\bar{E}^f_{t+1}(\pi_{t+1})] = E_{it}(p_t)$. Therefore, our guess is fully satisfied. ■

Using the lemma, we can derive Proposition 1.

For results (i)-(iii) and for the first part of (iv), we use y_t and π_t as defined in Lemma 1 and use the fact that $0 < \delta^m_{0n} < 1$, $0 < \delta^m_{1n} < 1$ and $0 < \delta^g_{0n} < 1$ for $n = a, b$ and $m = c, f$. The second part of (iv) derives from the fact that the effect of demand-noise shocks on inflation depends on the sign of $\delta^f_{0b} - \theta\kappa\varphi\delta^f_{1b}\delta^g_{0b}$, which is of the same sign as $\sigma_b^{-2} + \sigma_{0b}^{-2} - \theta\kappa\varphi(\sigma^f_{1b})^{-2}$. The permanent and temporary effect of shocks come from the nature of u^a_t, ϵ^b_t, e^a_t and e^b_t.

1.5.4 Proof of Proposition 2 and of Corollary 2.1

Note that, because s^a_t and s^b_t are part of the common information set, Lemma 1 implies

$$\begin{aligned} \bar{E}^s_t y_t - y_t &= \delta^c_{1a}\left(\bar{E}^s_t\epsilon^a_t - \epsilon^a_t\right) + \left(\bar{E}^s_t\epsilon^b_t - \epsilon^b_t\right) \\ \bar{E}^s_t\pi_t - \pi_t &= \kappa\left[-(1-\delta^c_{1a})\left(\bar{E}^s_t\epsilon^a_t - \epsilon^a_t\right) + \tfrac{\theta\delta^f_{1b}}{1-(1-\theta)\delta^f_{1b}}\left(\bar{E}^s_t\epsilon^b_t - \epsilon^b_t\right)\right] \end{aligned} \tag{A28}$$

The surveyors' average expectation errors on output and inflation depend on their average expectation errors on fundamental shocks $\bar{E}_t^s\epsilon_t^n - \epsilon_t^n$, $n = a, b$. We have $\bar{E}_t^s\epsilon_t^n - \epsilon_t^n = -(1 - \delta_{0n}^s - \delta_{1n}^s)\epsilon_t^n + \delta_{0n^s}e_t^n$, with $\delta_{0n}^s = (\sigma_{0n})^{-2}/[(\sigma_n)^{-2} + (\sigma_{0n})^{-2} + (\sigma_{1n}^s)^{-2}]$ and $\delta_{1n}^s = (\sigma_{1n}^s)^{-2}/[(\sigma_n)^{-2} + (\sigma_{0n})^{-2} + (\sigma_{1n}^s)^{-2}]$ for $n = a, b$. Since $0 < \delta_{0n}^s + \delta_{1n}^s < 1$ and $0 < \delta_{0n}^s < 1$, then the fundamental affects the average error negatively while the noise affects it positively. This proves Proposition 2.

Now consider δ_{1a}^c and δ_{1b}^f in the absence of private information ($(\sigma_{1a}^f)^{-2} = \sigma_{1b}^{-2} = 0$), we would have $\delta_{1a}^c = \delta_{1b}^f = 0$, so that the expectation errors on output would not react to supply-related fundamental and noise shocks, and the expectation errors on inflation would not react to demand-related fundamental and noise shocks. This proves Corollary 2.1.

1.5.5 Proof of Corollary 2.2

Consider Lemma 1. Both y_t and π_t can be written as a function of fundamental shocks (ϵ_t^a and ϵ_t^b) and of noise shocks (e_t^a and e_t^b). Therefore, the expectation errors $\bar{E}_t^s y_t - y_t$ and $\bar{E}_t^s\pi_t - \pi_t$ can be written as functions of the expectation errors about fundamental shocks ($\bar{E}_t^s\epsilon_t^a - \epsilon_t^a$ and $\bar{E}_t^s\epsilon_t^b - \epsilon_t^b$) and about noise shocks ($\bar{E}_t^s e_t^a - e_t^a$ and $\bar{E}_t^s e_t^b - e_t^b$).

Note that, because s_t^a and s_t^b are *not* part of the common information set, we have $\bar{E}_t^s\epsilon_t^n - \epsilon_t^n = -(1 - \delta_{1n}^s)\epsilon_t^n$, with $\delta_{1n}^s = (\sigma_{1n}^s)^{-2}/(\sigma_n^{-2} + (\sigma_{1n}^s)^{-2})$, for $n = a, b$, while $\bar{E}_t^s e_t^n - e_t^n = -e_t^n$. The effect of fundamental and noise shocks on the expectation errors about output and inflation is therefore of the sign opposite to their effect on the variables themselves. While this does not change the effect of fundamental shocks, it alters the effect of noise shocks.

2 Numerical Simulation Method

In this section, we describe the numerical method to simulate the benchmark New Keynesian model. We consider the firms from island $i \in [0, 1]$, household $j \in [0, 1]$ and surveyor $k \in [0, 1]$. We simulate the system given by A21, A20 and A24:

$$\begin{array}{rcl} p_{it}^* & = & (1 - \beta\theta)E_{it}^f\left[p_t + (1 + \zeta)(c_t - u_t^a)\right] + \beta\theta E_{it}^f(p_{it+1}^*) \\ \pi_t & = & \frac{(1-\theta)(1-\beta\theta)(1+\zeta)}{\theta}\bar{E}_t^f\left(c_t - u_t^a)\right] + \beta\bar{E}_t^f\left(\pi_{t+1}\right) \\ & & +\frac{1-\theta}{\theta}[\bar{E}^f(\pi_t) - \pi_t] + \beta(1 - \theta)\bar{E}_t^f\left(p_{it+1}^* - p_{t+1}^*\right) \\ c_{jt} & = & E_{jt}^c\left\{c_{t+1}\right\} + E_{jt}^c\left\{\pi_{t+1}\right\} - \varphi E_t^g\left\{\pi_t\right\} + u_t^b \end{array} \tag{A29}$$

where we use $c_t = \int_0^1 c_{jt}dj$ and $p_t^* = \int_0^1 p_{it}^*di$.

Define ξ_{it} as follows:

$$\xi_t = \left(\left\{\Upsilon_{t-s}\right\}_{0\leq s\leq T-2}, u_{t-T}^a, u_{t-T}^b, \left\{\pi_{t-s}\right\}_{1\leq s\leq T-1}, p_{t-T}\right)'$$

where $\Upsilon_t = \Big(\epsilon_t^a, e_t^a, \epsilon_t^b, e_t^b, \lambda_{jt}^{ac}, \lambda_{it}^{bf}, \lambda_{kt}^{as}, \lambda_{kt}^{bs}\Big)$.

We make the guess that there exist vectors A_p and A_c satisfying:

$$p^*_{it} = A_p \xi_t$$

$$\pi_t = A_\pi \xi_t$$

$$c_{jt} = A_c \xi_t$$

Define X the matrix that selects the aggregate shocks from ξ_t. X is a diagonal matrix where the k^{th} term on the diagonal is 1 if the k^{th} term in ξ_t is an aggregate shock and 0 if it is an idiosyncratic shocks. We have:

$$p^*_t = A_p X \xi_t$$

$$c_t = A_c X \xi_t$$

We have $\xi_{t+1} = \Gamma \xi_t + \varsigma_{t+1}$ with

$$\Gamma = \left(\begin{array}{ccccccccccccccccc}
\multicolumn{4}{c}{\xleftrightarrow{\quad 8 \quad}} & \multicolumn{4}{c}{\xleftrightarrow{\quad 8\times(T-2) \quad}} & \multicolumn{2}{c}{\xleftrightarrow{\quad 2 \quad}} & \xleftrightarrow{1} & \multicolumn{5}{c}{\xleftrightarrow{\qquad T-2 \qquad}} & \xleftrightarrow{1} \\
0 & \cdots & \cdots & 0 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\
\vdots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\
0 & \cdots & \cdots & 0 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\
1 & 0 & \cdots & 0 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\
0 & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & 0 \\
\vdots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & 0 \\
0 & \cdots & 0 & 1 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\
0 & \cdots & \cdots & 0 & 1 & 0 & \cdots & 0 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\
\vdots & \cdots & \cdots & \vdots & 0 & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\
\vdots & \cdots & \cdots & \vdots & \vdots & \ddots & \ddots & 0 & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\
0 & \cdots & \cdots & 0 & 0 & \cdots & \cdots & 1 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\
0 & \cdots & \cdots & 0 & 0 & \cdots & \cdots & 0 & 1 & 0 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\
0 & \cdots & \cdots & 0 & 0 & \cdots & \cdots & 0 & 0 & \rho_b & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\
(& & & & & & & & & A_\pi X & & & & & & &) \\
0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 & 1 & 0 & \cdots & \cdots & 0 & 0 \\
\vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots & 0 & \ddots & \ddots & \ddots & \vdots & 0 \\
\vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \vdots & 0 \\
\vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \vdots & 0 \\
\vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots & 0 & \cdots & \cdots & 0 & 1 & 0 \\
0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 & 0 & \cdots & \cdots & 0 & 1 & 1
\end{array}\right)$$

$$\varsigma_t = (\Upsilon_t, 0, \cdots, 0)'$$

The signals received by firm i, household j and surveyor k are linear transformations of ξ_t. They can be summarized by matrices H^c, H^f and H^s such that

$$S_{it}^f = H^f \xi_t$$

$$S_{jt}^c = H^c \xi_t$$

$$S_{kt}^f = H^s \xi_t$$

where S_{jt}^c is the vector of signals received by household j, S_{it}^f is the vector of signals received by firm i and S_{kt}^s is the vector of signals received by surveyor k. The central bank has a similar information structure with

$$S_t^g = H^g \xi_t$$

where S_t^g is the vector of signals received by the central bank.

Define

$$K^m = \Sigma H^{m'} (H^m \Sigma H^{m'})^{-1}$$

$m = c, f, s, g$, where Σ is the matrix of variance-covariance of ξ_t. We have

$$E_{jt}^c(\xi_t) = K^c S_{jt}^c = K^c H^c \xi_t$$

$$E_{it}^f(\xi_t) = K^f S_{it}^f = K^f H^f \xi_t$$

$$E_{kt}^s(\xi_t) = K^s S_{kt}^s = K^s H^s \xi_t$$

$$E_t^g(\xi_t) = K^g S_t^g = K^g H^g \xi_t$$

We therefore have

$$E_{it}^f(c_t) = A_c X K^f H^f \xi_t$$

$$\bar{E}_t^f(p_{it+1}^*) = A_p \Gamma K^f H^f X \xi_t$$

$$\bar{E}_t^f(p_{t+1}^*) = A_p X \Gamma K^f H^f X \xi_t$$

$$\bar{E}_t^f(\pi_t) = A_\pi K^f H^f X \xi_t$$

$$\bar{E}_t^f(\pi_{t+1}) = A_\pi \Gamma K^f H^f X \xi_t$$

$$\bar{E}_t^f(c_t) = A_c K^f H^f X \xi_t$$

$$E_{it}^c(c_{t+1}) = A_c X \Gamma K^c H^c \xi_{it}$$

$$E_{it}^c(\pi_{t+1}) = A_p X \Gamma K^c H^c \xi_t$$

$$E_t^g(\pi_t) = A_\pi K^g H^g \xi_t$$

Replacing these expressions in A29 and rearranging, we get $\begin{pmatrix} A_c & A_p & A_\pi \end{pmatrix} \Omega = \Delta$ with

$$\Omega = \begin{pmatrix} Id - \Gamma K^c H^c & ; & -(1-\beta\theta)(1+\zeta)K^f H^f & ; & -\kappa K^f H^f X \\ 0 & ; & Id - \beta\theta\Gamma K^f H^f & ; & -(1-\theta)\beta\Gamma(Id - X)K^f H^f X \\ -\Gamma K^c H^c + \varphi K^g H^g & ; & -(1-\beta\theta)K^f H^f & ; & Id - \beta\Gamma K^f H^f X - [(1-\theta)/\theta](Id - K^f H^f)X \\ \end{pmatrix}$$

$$\Delta = \begin{pmatrix} U^b & ; & -(1-\beta\theta)((1+\zeta)U^a - P_0)K^f H^f & ; & -\kappa U^a \end{pmatrix}$$

and P_0, U^a, U^b, are such that $p_{t-1} = P_0\xi_t$, $u_t^a = U^a\xi_{it}$, $u_t^b = U^b\xi_{it}$. Id is the identity matrix.

We therefore have

$$\begin{pmatrix} A_c & A_p & A_\pi \end{pmatrix} = \Delta\Omega^{-1}$$

Note though that Ω depends on Γ and that Γ depends on A_p, so we denote $\Omega(A_p)$ and $\Gamma(A_p)$. We therefore initialize A_p to A_{p0} and derive $\Gamma(A_{p0})$ and $\Omega(A_{p0})$. Then $A_{p1} = \Delta\Omega(A_{p0})^{-1}$. We iterate N times until A_{pN} is sufficiently close to A_{pN-1}, and obtain this way our numerical solution.

3 Model's Estimation

In this section, we describe the estimation strategy of the New Keynesian model and we provide some robustness exercises.

3.1 Estimation Strategy

Using the benchmark SVAR model estimated in Section 3 of the main text, we first compute for each accepted draw $\hat{\Upsilon}_j^{x,\eta} \equiv \partial x_{t+j}/\partial\eta_t$, the response of variable x_{t+j} to shock η_t with $\eta_t = \{\varepsilon_t^a$, ϵ_t^a, ε_t^b, $\epsilon_t^b\}$. Then, by denoting $\hat{\sigma}_\Upsilon^{x,\eta}$, the empirical standard deviation of $\hat{\Upsilon}_j^{x,\eta}$ over five quarters, the model's parameters are estimated such that theoretical second-order moments are as close as possible to their median empirical counterpart. Let the vectors $\hat{\Phi}$ and $\Phi(\psi_k)$, with $k = \{s, d\}$, denote the VAR-based and the model-based second-order moments, respectively. Parameter estimates $\hat{\psi}_k$ fulfil

$$\hat{\psi}_k = \arg\min_{\psi_k \in \Psi_i} \; [\Phi^m(\psi_k) - \hat{\Phi}]'\hat{W}[\Phi^m(\psi_k) - \hat{\Phi}], \text{ for } k = \{s, d\} \tag{A30}$$

where $\hat{W}$ is a diagonal matrix with the inverse of the empirical variances of each element of $\hat{\Phi}$ along the diagonal. Since supply and demand shocks and the corresponding noise are orthogonal, we can estimate separately the supply-side and the demand-side parameters. The J-stat reported in Tables 4 and 5 of the main paper (as well as Tables A2 to A4 here) corresponds to the eucledian distance between the SVAR-based and the model-based moments. We report in the main text the p-value of the J-stat for the benchmark estimation. We compute the p-value as following: For eah successul draw in the SVAR estimation, we re-estimate the benchmark theoretical model and deduce the distribution of the J-stat. Following Fève et al. (2009), we then apply a kernel Gaussian kernel with positive support to the simulated J-stat and apply a a piecewise cubic spline interpolation procedure to compute the p-value. The null hypothesis being tested is that the J-stat is zero.

3.2 Additional Estimation Results

Table A2 shows the results of the estimation of the demand-side model when only output and inflation conditional volatilities are matched (i.e. the errors' conditional volatilities are not matched). The estimated parameters are not dramatically different from Tables 4 in the main text, except from the signal-to-noise ratio of firms' private signals, which is one order of magnitude smaller. Here, constraining firms' signal precision to be zero does not significantly increase the J-stat of the estimation. However, the non-matched moments are poorly replicated. In particular, the conditional volatility of the errors are close to zero, which contrasts with the large levels estimated in the data. This suggests that taking into account the errors is important to capture firms' private information, as explained in the main text.

Tables A3 and A4, provides estimation results when we change the information set of agents. The first column corresponds to the baseline estimation as reported in Tables 4 and 5 of the main paper. The second column is also reported in Tables 4 and 5 of the main paper and shows the results when we constraint the signal-to-noise ratio of the households's private signals on supply (Table A3) and the signal-to-noise ratio of the firm's private signals on demand (Table A4) to be zero. As explained in the paper, private information for households about supply and firms about demand is crucial to match expectation errors since expectation errors contain information that help to infer correctly the level of private information. The third column in Tables A3 and A4 show the estimation results when the surveyor has no private information. We find that the goodness-of-fit of the model is not affected by this assumption, which confirms that surveyors' information is not crucial to explain the conditional volatilities of expectation errors (on contrary to decision-makers' private information).Finally, the last column in Tables A3 and A4 show the estimation results when the central bank observes inflation. As mentionned in the main text, the supply-side model does not perform better in this informed central bank case ($J-stat = 5.5$ in the baseline and $J-stat = 7$ in the alternative case). When it comes to the demand-side model estimation result, the goodness-of-fit of the informed central bank is worse ($J-stat = 5$ in the baseline and $J-stat = 14$ in the alternative case). Therefore, our baseline assumption regarding the information set of the central bank seems to be relevant.

Table A2. Demand-related parameters: output and inflation moments only

	Data	Baseline	No firms priv. info $(\sigma_{b1}^{f})^{-2} = 0$
Estimated parameters			
σ_b^2		0.74	0.75
σ_{b0}^2		0.71	0.70
$\sigma_{b0}^{-2}/\sigma_b^{-2}$		1.00	1.10
$(\sigma_{b1}^{f})^{-2}/\sigma_b^{-2}$		0.14	(constrained)
$(\sigma_{b1}^{s})^{-2}/\sigma_b^{-2}$		0.52	0.43
J-stat		0.19	0.32
Matched moments			
$\sigma(\Delta y_t \vert \epsilon_t^b)$	1.10 [0.81,1.3]	1.20	1.10
$\sigma(\Delta y_t \vert e_t^b)$	1.50 [0.84,2]	1.50	1.40
$\sigma(\pi_t \vert \epsilon_t^b)$	1.10 [0.81,1.3]	1.10	1.10
$\sigma(\pi_t \vert e_t^b)$	0.41 [0.28,0.65]	0.42	0.48
$\sigma(\bar{E}^s(\Delta y_t) - \Delta y_t \vert \epsilon_t^b)$	0.87 [0.5,1.3]	0.75	0.74
$\sigma(\bar{E}^s(\Delta y_t) - \Delta y_t \vert e_t^b)$	0.98 [0.55,1.3]	1.00	1.00
$\sigma(\bar{E}^s(\pi_t) - \pi_t \vert \epsilon_t^b)$	0.37 [0.2,0.6]	0.023	0.00
$\sigma(\bar{E}^s(\pi_t) - \pi_t \vert e_t^b)$	0.36 [0.24,0.49]	0.044	0.00

Note: The Baseline case corresponds to the estimation of the full model. The No firm priv. info case corresponds to the estimation of the model where σ_{b1}^{f} is constrained to be zero. The empirical moments matched in the estimation procedure are computed from the median IRFs of variables to shocks over the first five quarters. The values in square brakets corresponds to the moments computed from the 16th and 84th percentile IRFs.

Table A3. Supply-related parameters: Additional exercises

	Data	Baseline	No HH priv. info $(\sigma^c_{a1})^{-2}=0$	No surv. priv. info $(\sigma^s_{a1})^{-2}=0$	Informed CB
Estimated parameters					
σ^2_a		6.8	5.2	7.3	9.1
σ^2_{a0}		8.8	2.0	8.7	6.4
$\sigma^{-2}_{a0}/\sigma^{-2}_a$		0.77	2.6	0.84	1.4
$(\sigma^c_{a1})^{-2}/\sigma^{-2}_a$		1.4	(constrained)	1.4	3.6
$(\sigma^s_{a1})^{-2}/\sigma^{-2}_a$		0.0038	0	(constrained)	0.0022
J-stat		5.5	30	5.4	7
Matched moments					
$\sigma(\Delta y_t \vert \epsilon^a_t)$	2.2 [1.82,6]	2.00	1.80	2.10	2.60
$\sigma(\Delta y_t \vert e^a_t)$	0.66 [0.46,1]	1.10	1.40	1.20	0.85
$\sigma(\pi_t \vert \epsilon^a_t)$	0.39 [0.2,0.74]	0.40	0.26	0.40	0.21
$\sigma(\pi_t \vert e^a_t)$	0.54 [0.23,0.89]	0.49	0.55	0.40	0.21
$\sigma(\bar{E}^s(\Delta y_t) - \Delta y_t \vert \epsilon^a_t)$	0.56 [0.39,0.76]	0.47	0.00	0.47	0.57
$\sigma(\bar{E}^s(\Delta y_t) - \Delta y_t \vert e^a_t)$	0.83 [0.59,1.1]	0.95	0.00	0.95	1.20
$\sigma(\bar{E}^s(\pi_t) - \pi_t \vert \epsilon^a_t)$	0.35 [0.24,0.53]	0.40	0.26	0.40	0.21
$\sigma(\bar{E}^s(\pi_t) - \pi_t \vert e^a_t)$	0.74 [0.54,0.87]	0.49	0.55	0.50	0.29

Note: The Baseline case corresponds to the estimation of the full model. The No HH priv. info case corresponds to the estimation of the model where σ^c_{a1} is constrained to be zero. The No surv. priv. info case corresponds to the estimation of the model where σ^s_{a1} is constrained to be zero. The Informed CB case corresponds to the model where the Taylor rule depends on current inflation. The empirical moments matched in the estimation procedure are computed from the median IRFs of variables to shocks over the first five quarters. The values in square brakets corresponds to the moments computed from the 16th and 84th percentile IRFs.

Table A4. Demand-related parameters: Additional exercises

	Data	Baseline	No firms priv. info $(\sigma_{b1}^{f})^{-2} = 0$	No surv. priv. info $(\sigma_{b1}^{s})^{-2} = 0$	Informed CB
Estimated parameters					
σ_b^2		0.69	0.75	0.63	0.037
σ_{b0}^2		0.52	0.70	0.43	0.012
$\sigma_{b0}^{-2}/\sigma_b^{-2}$		1.3	1.1	1.5	3.1
$(\sigma_{b1}^{f})^{-2}/\sigma_b^{-2}$		1.1	(constrained)	1.1	2.1
$(\sigma_{b1}^{s})^{-2}/\sigma_b^{-2}$		0.29	0.42	(constrained)	1.9
J-stat		5	12	5.1	14
Matched moments					
$\sigma(\Delta y_t \vert \epsilon_t^a)$	1.10 [0.81,1.3]	1.1	1.1	1	0.16
$\sigma(\Delta y_t \vert e_t^a)$	1.50 [0.84,2]	1.5	1.4	1.4	0.24
$\sigma(\pi_t \vert \epsilon_t^a)$	1.10 [0.81,1.3]	1.2	1.1	1.1	0.27
$\sigma(\pi_t \vert e_t^a)$	0.41 [0.28,0.65]	0.14	0.48	0.15	0.036
$\sigma(\bar{E}^s(\Delta y_t) - \Delta y_t \vert \epsilon_t^a)$	0.87 [0.5,1.3]	0.79	0.75	0.77	0.07
$\sigma(\bar{E}^s(\Delta y_t) - \Delta y_t \vert e_t^a)$	0.98 [0.55,1.3]	1.2	1.1	1.3	0.14
$\sigma(\bar{E}^s(\pi_t) - \pi_t \vert \epsilon_t^a)$	0.37 [0.2,0.6]	0.13	0	0.13	0.012
$\sigma(\bar{E}^s(\pi_t) - \pi_t \vert e_t^a)$	0.36 [0.24,0.49]	0.26	0	0.27	0.028

Note: The Baseline case corresponds to the estimation of the full model. The No firms priv. info case corresponds to the estimation of the model where σ_{b1}^{f} is constrained to be zero. The No surv. priv. info case corresponds to the estimation of the model where σ_{b1}^{s} is constrained to be zero. The Informed CB case corresponds to the model where the Taylor rule depends on current inflation. The empirical moments matched in the estimation procedure are computed from the median IRFs of variables to shocks over the first five quarters. The values in square brakets corresponds to the moments computed from the 16th and 84th percentile IRFs.

4 Checking the Validity of Sign Restrictions

Here we simulate an extended version of the model on a wide range of parameter values in order to assess the validity of our sign restrictions. In this extended version, we allow firms to make quantity decisions and we introduce a private signal for the central bank. We also check whether other types of demand shocks (monetary, government spending) lead to the same sign restrictions, and whether other supply shocks (temporary TFP shocks, mark-up shocks) could be confused with demand or demand noise shocks with our methodology.

4.1 Model's Extension

Quantity decisions by firms In our baseline setup, demand-noise shocks have a negative effect on aggregate demand because firms set higher prices. This aggregate decline in demand hinges on the fact that firms make only pricing decisions. Here we allow firms to make quantity decisions as well. The effect on aggregate demand can then become positive.

To introduce quantity decisions by firms, we assume that firm j form island i uses a quantity X_{ijt} of final good in the individual good production function. The production function A4 then becomes

$$Y_{ijt} = X_{ijt}^{\alpha}(A_t N_{ijt})^{1-\alpha}, \tag{A31}$$

with $0 < \alpha < 1$. One can think of X_{ijt} as intermediate input or as an investment that fully depreciates from period to period. Firms make plans on X_{ijt} at the second stage, at the same time when they set prices, and shop at the third stage, on island i. Hence, the log-linearized equilibrium equation for island i is modified as follows

$$y_{it} = (1-\alpha)c_{k(i,t)t} + \alpha x_{it}. \tag{A32}$$

where $\alpha = X/Y$ is the steady-state share of intermediate input in aggregate demand.

The optimal choice of intermediate input satisfies

$$x_{ijt} = p_{ijt} + E_{it}^{f}(y_{ijt}) - p_{it} \tag{A33}$$

Note that firms on island i share the same information, so p_{it} is common knowledge. Crucially, the demand for intermediate input depends on firms expectation on the demand for their individual good. Taking the island average, and using the fact that $\int_0^1 p_{ijt}dj = p_{it}$, we obtain

$$x_{it} = E_{it}^{f}(y_{it}). \tag{A34}$$

Crucially, the demand for intermediate input depends on firms' expectation on the demand for the final good. Combining Equations A34 and A32, we get that $x_{it} = E_{it}^{f}(c_{k(i,t)t})$, so local demand now depends not only on local consumption, but also on firms' expectations on consumption. Aggregate demand then follows

$$y_t = (1-\alpha)c_t + \alpha \bar{E}_t^f(c_t), \tag{A35}$$

This is obtained by aggregating A32 with $x_{it} = E_{it}^f(c_{k^c(i,t)t})$. Under Assumption 1, consumption of household $k(i,t)$ is not conditional on the price p_{it} and depends only on the information specific to island $k(i,t)$, so the firm can at best forecast c_t: $E_{it}^f(c_{k^c(i,t)t}) = E_{it}^f(c_t)$.

The key difference is that now aggregate demand now depends not only on aggregate consumption but also on the firms' expectations on aggregate consumption.

The aggregate Euler equation stays unchanged, we simply have to replace y_t by c_t in A18.

The aggregate Phillips curve is obtained through the firm's new pricing equation:

$$p_{ijt}^* = p_{it}^* = (1-\beta\theta)E_{it}^f[\alpha p_{it} + (1-\alpha)(w_t - u_t^a)] + \beta\theta E_{it}^f(p_{it+1}^*) \tag{A36}$$

The marginal cost now depends to a lower extent on the expected nominal marginal cost of labor w_{it}, but it now depends also on the intermediate input cost p_{it}.

Consider the expected nominal marginal cost of labor $w_t - u_t^a$. Firms know u_t^a by assumption, but not w_t. Plugging the aggregated log-linear version of the production equation A31 $y_t = \alpha x_t + (1-\alpha)(u_t^a + n_t)$ with $x_t = \bar{E}^f(c_t)$ and the aggregated resource equation A35 $y_t = (1-\alpha)c_t + \alpha\bar{E}_t^f(c_t)$ into the labor supply equation A14, we can see that the nominal wage w_t is equal to $p_t + c_t + [\zeta/(1-\alpha)][(1-\alpha)c_t + (\alpha-\alpha)\bar{E}_t^f(c_t) - (1-\alpha)u_t^a]$, so $w_t = p_t + (1+\zeta)\,c_t - \zeta u_t^a$ where c_t is the average consumption. Therefore,

$$E_{it}^f(w_t) \quad = \quad E_{it}^f\left[p_t + (1+\zeta)\,c_t - \zeta u_t^a\right]$$

Therefore, A36 writes

$$p_{ijt}^* = p_{it}^* \quad = \quad (1-\beta\theta)\Big\{\alpha p_{it} + (1-\alpha)E_{it}^f\left[p_t + (1+\zeta)(c_t - u_t^a)\right]\Big\} + \beta\theta E_{it}^f(p_{it+1}^*) \tag{A37}$$

The aggregate Euler equation and the aggregate Phillips curve can then be written as a function of c_t and π_t only:

$$c_t = \bar{E}_t^c\left\{c_{t+1} + \pi_{t+1}\right\} - \varphi E_t^g\left\{\pi_t\right\} + u_t^b. \tag{A38}$$

$$\begin{aligned}\pi_t \quad = \quad & \kappa(1-\alpha)\left(\bar{E}_t^f\left\{c_t\right\} - u_t^a\right) + \beta\bar{E}_t^f\left\{\pi_{t+1}\right\} \\ & + \tfrac{1-\theta}{\theta}[1-\alpha(1-\beta\theta)]\left[\bar{E}_t^f\left\{\pi_t\right\} - \pi_t\right] \\ & + (1-\theta)\beta\bar{E}_t^f\left\{p_{it+1}^* - p_{t+1}^*\right\}.\end{aligned} \tag{A39}$$

then we use A35 to determine y_t. The Euler equation is the same as before, while the Phillips curve is slightly different. As the share of labor $1-\alpha$ is lower than one, inflation reacts less to the expected marginal cost of labor $\bar{E}_t^f\left\{c_t\right\} - u_t^a$. Notice that when $\alpha = 0$, this system boils down to (20)-(22) in the manuscript, with $y_t = c_t$.

Central bank's information and monetary policy We also make the information set of the central bank more general, by allowing the central bank to observe additional signals $x_t^{ng} = u_t^n + \lambda_t^{ng}$, with $\lambda_t^{ng} \sim \mathcal{N}(0, (\sigma_{1n}^g)^2)$, for $n = a, b$. These signals are private to the central bank. This extension nests our baseline model where all the information of the central bank is public, when σ_{1n}^g goes to infinity. It also nests a perfectly informed central bank when $\sigma_{1n}^g = 0$, which is equivalent to letting the central bank observe inflation perfectly.

Additionally, we assume that the central bank follows the more general Taylor rule:

$$i_t = \bar{\imath} + \varphi E_t^g(\pi_t) + \phi E_t^g(x_t), \tag{A40}$$

where x_t is the output gap defined as follows: $x_t = y_t - u_t^a$.

4.2 Simulations of the Extended Model

We extend our numerical simulation method by extending the vector of states ξ_t to include λ_t^{ag} and λ_t^{bg}, by modifying the set of signals available to the central bank (extending H^g), and solving the system A35, A38, A37 and A39.

The preference and technology parameters are set to standard values, as described in Section 4.2 of the main paper, and the magnitude of fundamental shocks σ_a and σ_b are normalized to 1. We however consider a broad range of parameters for the information-related parameters, for the share of intermediate input in production and for the coefficient of the output gap in the Taylor rule ϕ. These ranges are described in Table A5. Our procedure is as follows. We draw 1000 different parameter combinations drawn from independent uniform distributions on the considered parameters. For each draw, we simulate the model and compute the impact IRFs for output growth, inflation and the average output growth and inflation survey expectation errors. Table A6 then reports signs of the impact responses which are predominant over all our draws as well as the percentage of impact IRFs which are of this sign.

Table A6 shows that our sign restrictions are satisfied across all simulations for the supply, supply noise and demand shocks. For demand noise shocks, the sign restrictions are satisfied for the expectation errors as well. Regarding the positive response of inflation, it is satisfied in 98% of the simulations. This makes us confident that our sign restrictions are solid. However, we do not know exactly where in the spectrum of parameters we are, so we cannot exclude that demand noise shocks have a negative effect on inflation. However, our empirical exercise shows that our results are only slightly affected when we relax the restriction on the response of inflation to demand noise.

4.3 Adding Shocks

Here we perform the same exercise for monetary and government spending shocks, and check whether these shocks behave like our preference-based demand shock and whether their cor-

Table A5. Sign Restrictions Validity: Parameters range for simulation

	Parameter	Range	Parameter	Range
Baseline Model				
	σ_a^2	1	σ_b^2	1
	σ_{a0}^{-2}	$[0, 10]$	σ_{b0}^{-2}	$[0, 10]$
	$(\sigma_{a1}^c)^{-2}$	$[0, 10]$	$(\sigma_{b1}^f)^{-2}$	$[0, 10]$
	$(\sigma_{a1}^s)^{-2}$	$[0, 10]$	$(\sigma_{b1}^s)^{-2}$	$[0, 10]$
	$(\sigma_{a1}^g)^{-2}$	$[0, 10]$	$(\sigma_{b1}^g)^{-2}$	$[0, 10]$
	τ	$[0, 1]$	τ	$[0, 1]$
	ϕ	$[0, 1]$	ϕ	$[0, 1]$
Adding Shocks Model				
	σ_v^2	1	σ_g^2	1
	σ_{v0}^{-2}	$[0, 10]$	σ_{g0}^{-2}	$[0, 10]$
	$(\sigma_{v1}^f)^{-2}$	$[0, 10]$	$(\sigma_{g1}^f)^{-2}$	$[0, 10]$
	$(\sigma_{v1}^s)^{-2}$	$[0, 10]$	$(\sigma_{g1}^s)^{-2}$	$[0, 10]$
	$(\sigma_{v1}^g)^{-2}$	$[0, 10]$	$(\sigma_{g1}^g)^{-2}$	$[0, 10]$
	τ	$[0, 1]$	τ	$[0, 1]$
	ϕ	$[0, 1]$	ϕ	$[0, 1]$
Model with Temporary Supply Shocks				
	σ_a^2	1		
	σ_{a0}^{-2}	$[0, 10]$		
	$(\sigma_{a1}^f)^{-2}$	$[0, 10]$		
	$(\sigma_{a1}^s)^{-2}$	$[0, 10]$		
	$(\sigma_{a1}^g)^{-2}$	$[0, 10]$		
	$(\sigma_{a2})^{-2}$	$[0, 10]$		
	τ	$[0, 1]$		
	ϕ	$[0, 1]$		

Note: The Baseline case corresponds to the simulation of the benchmark New Keynesian model. The "Adding shocks model" case corresponds to the model with additional shocks, as described in Section 4.3. The "Model with temporary supply shock" case corresponds to the model where supply shocks are not permanent anymore, as described in Section 4.4. Each model is simulated by drawing 1000 different values of parameters from independant uniform distribution over the range provided in this table.

Table A6. Sign Restrictions Validity: Sign of IRFs on impact across simulations

Baseline Model	Δy_t	π_t	$\bar{E}^s_t(\Delta y_t) - \Delta y_t$	$\bar{E}^s_t(\pi_t) - \pi_t$
ϵ^a_t	> 0 (100)	< 0 (100)	< 0 (100)	> 0 (100)
e^a_t	> 0 (100)	> 0 (100)	> 0 (100)	< 0 (100)
ϵ^b_t	> 0 (100)	> 0 (100)	< 0 (100)	< 0 (100)
e^b_t	< 0 (91)	> 0 (98)	> 0 (100)	> 0 (100)
Adding Shocks Model				
ϵ^v_t	> 0 (100)	> 0 (100)	< 0 (100)	< 0 (100)
e^v_t	< 0 (61)	> 0 (100)	> 0 (100)	> 0 (100)
ϵ^g_t	> 0 (96)	> 0 (98)	< 0 (96)	< 0 (97)
e^g_t	< 0 (59)	> 0 (96)	> 0 (96)	> 0 (97)
Model with Temporary Supply Shocks				
ϵ^a_t	> 0 (100)	< 0 (100)	< 0 (100)	> 0 (100)
e^a_t	> 0 (100)	> 0 (100)	> 0 (100)	< 0 (100)
μ^a_t	> 0 (100)	< 0 (100)	< 0 (100)	> 0 (100)

Note: The Baseline case corresponds to the simulation of the benchmark New Keynesian model. The "Adding shocks model" case corresponds to the model with additional shocks, as described in Section 4.3. The "Model with temporary supply shock" case corresponds to the model where supply shocks are not permanent anymore, as described in Section 4.4. A >0 (<0, resp.) means that the IRF of the variable to a shock is predominantly positive (negative, resp.) on impact over the 1000 simulations where parameters are drawn from a uniform distribution as described in Table A5. The value in brackets corresponds to the percentage of IRFs across simulations which are of the reported sign.

responding noise behaves like our preference-based demand noise shock. We therefore check whether our methodology can capture a broad array of demand shocks.

We introduce aggregate monetary policy shocks and government spending shocks. More specifically, the Taylor rule A6 is modified as follows:

$$i_t = i + \varphi E_t^g(\pi_t) - u_t^v, \tag{A41}$$

where u_t^v is a monetary policy shifter.[6] We introduce a government who finances spending G_t through taxes: $G_t = T_t$, where $G_t = \bar{g} Y e^{u_t^g}$ where Y is the steady-state output. We assume that the government purchases equal amounts of goods in the different islands and that households pay equal lump-sum taxes. The resource constraint A17 becomes:

$$y_{it} = (1 - \alpha - \bar{g}) c_{k(i,t)t} + \alpha x_{it} + \bar{g} u_t^g. \tag{A42}$$

We assume that u_t^n, $n = v, g$ follow autoregressive processes: $u_t^n = \rho_n u_{t-1}^n + \epsilon_t^n$ where $\epsilon_t^n \sim \mathcal{N}(0, \sigma_n^2)$, $n = v, g$.

Regarding information, all agents (households, firms, surveyors, central bank) in the economy observe public signals s_t^n on the fundamental shock u_t^n, $n = v, g$, of the form described in A8, where $e_t^n \sim \mathcal{N}(0, \sigma_{0n}^2)$. Besides, households, firms and surveyors receives a private signal on u_t^n, $n = v, g$, of the form $x_{it}^{nm} = u_t^n + \lambda_{it}^{nm}$, where $\lambda_{it}^{nm} \sim \mathcal{N}(0, (\sigma_{1n}^m)^2$ satisfies $\int_0^1 \lambda_{it}^{nm} di = 0$, for $n = v, g$ and $m = c, f, s$. Otherwise, the information structure stays unchanged. The difference with the preference shock is that the monetary and government spending shocks are not directly observed by households. As in our baseline model, shocks are realized and signals are revealed in stage 2.

Now, the demand for intermediate input depends on firms' expectation on the demand for the final good that arises from households, but also from the government. Combining Equations A34 and A42, we get that $x_{it} = \frac{1-\alpha-\bar{g}}{1-\alpha} E_{it}^f(c_{k(i,t)t}) + \frac{\bar{g}}{1-\alpha} E_{it}(u_t^g)$. Replacing in A42 and aggregating across islands, we obtain the aggregate resource constraint:

$$y_t = (1 - \alpha - \bar{g}) \left(c_t + \frac{\alpha}{1-\alpha} \bar{E}_t^f(c_t) \right) + \bar{g} \left(u_t^g + \frac{\alpha}{1-\alpha} \bar{E}_t^f(u_t^g) \right). \tag{A43}$$

The optimal pricing equation A36 is still valid. Plugging the aggregated log-linear version of the production equation A31 $y_t = \alpha x_t + (1-\alpha)(u_t^a + n_t)$ and the aggregated resource equation A42 $y_t = (1 - \alpha - \bar{g}) c_t + \alpha x_t + \bar{g} u_t^g$ into the labor supply equation A14, we can see that the nominal wage w_t is equal to $p_t + c_t + [\zeta/(1-\alpha)][(1-\alpha-\bar{g})c_t + \bar{g} u_t^g - (1-\alpha) u_t^a]$. Therefore, A36 writes as

$$p_{ijt}^* = p_{it}^* \;=\; (1 - \beta\theta) \left\{ \alpha p_{it} + (1-\alpha) E_{it}^f \left[p_t + (1+\zeta)(c_t - u_t^a) + \tfrac{\zeta \bar{g}}{1-\alpha}(u_t^g - c_t) \right] \right\} + \beta\theta E_{it}^f(p_{it+1}^*) \tag{A44}$$

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[6] This shifter can be viewed as a change in velocity or in the term premium. Alternatively, we could add additional noisy signals received by the central bank on the fundamentals of the economy.

and the Phillips curve becomes:

$$\begin{aligned}\pi_t \;=\;& \kappa(1-\alpha)\left(\bar{E}_t^f\left\{c_t\right\} - u_t^a + \tfrac{\zeta\bar{g}}{(1+\zeta)(1-\alpha)}(\bar{E}_t^f\left\{u_t^g\right\} - \bar{E}_t^f\left\{c_t\right\})\right) + \beta\bar{E}_t^f\left\{\pi_{t+1}\right\} \\ & +\tfrac{1-\theta}{\theta}[1-\alpha(1-\beta\theta)]\left[\bar{E}_t^f\left\{\pi_t\right\} - \pi_t\right] \\ & +(1-\theta)\beta\bar{E}_t^f\left\{p^*_{it+1} - p^*_{t+1}\right\}.\end{aligned} \tag{A45}$$

Finally, The aggregate Euler Equation is modified as follows:

$$c_t = \bar{E}_t^c\left\{y_{t+1} + \pi_{t+1}\right\} - \varphi E_t^g\left\{\pi_t\right\} + u_t^b + u_t^v. \tag{A46}$$

Simulation results We extend our numerical simulation procedure on the system A43, A44, A45 and A46. We normalize $\sigma_v = \sigma_g = 1$ and consider a broad range for the related information parameters, as described in Table A5. The results are summarized in Table A6.

The monetary policy and government spending shocks both shift aggregate demand, just like the preference shock. Consistently, the predictions applying to the preference shock mostly apply to the monetary shock and government spending shocks.

However, there are some differences. First, monetary policy shocks generate more often a positive response of output to demand noise shocks than preference shocks, and inflation responds systematically in a positive manner to demand noise shocks. This comes from the fact that monetary policy shocks are assumed not to be perfectly observed by households, contrary to preference shocks. As a result, when observing a positive signal on monetary policy, household anticipate a persistent decline in the interest rate, which stimulates aggregate demand. This, consistently, accentuates the propensity of firms to increase their prices upon receiving a positive signal on demand. Second, the response of output and inflation to government spending shocks is not systematically positive. This is because government spending can crowd out consumption.

Our empirical procedure therefore identifies a large set of demand shocks, and not only preference shocks.

4.4 Temporary Technology Shocks

We consider here a variant of the model where we suppose that the level of technology u_t^a can be written as a function of a permanent component x_t and a temporary one μ_t:

$$u_t^a = x_t + \mu_t \tag{A47}$$

where x_t follows a random walk $x_t = x_{t-1} + \epsilon_t^a$, and $\mu_t \sim \mathcal{N}(0, \sigma_{2a}^2)$. We assume now that u_t^a is observed by firms, x_t is not. As before, agents receive a public signal on u_t^a, $s_t^a = u_t^a + e_t^a$ and households receive a private signals on u_t^a, $x_{it}^a = u_t^a + \lambda_{it}^{ac}$. Agents learn past values of x after T periods. The rest of the model is identical to the baseline.

A29 still apply. Only the process for u_t^a and the information structure are modified. We perform the same exercise as before. We normalize σ_a to one, and assume a broad range for the information parameters and for the temporary shock's variance σ^2_{2a}, as described in Table A5. The results are reported in Table A6.

Simulation results The effect of supply noise shocks is the same as in the baseline case, which is expected. Notably, on impact, the temporary supply shock generates the same qualitative responses of output, inflation and the errors as a permanent supply shock. It has a negative effect on inflation because it decreases the current marginal cost and a positive effect on output because it increases the households' expectations about the permanent component of technology x_t. Just as in the case of permanent shocks, the deflation is underestimated by surveyors, because they cannot perfectly apprehend the current state of technology u^a_t that drives prices downward. They also underestimate the rise in aggregate demand, because μ^a_t, which shifts households' expectations about x_t, is not directly observed by them.

In terms of identification, we can see that, because temporary supply shocks generate a negative correlation between the errors, they can easily be confused with supply noise shocks. This explains why, when relaxing the restriction on the reaction of output to supply noise, we found non-significant effects: since negative temporary supply shocks produce the same signs for the errors as a positive supply noise shock, the effect of supply noise shocks on output is biased downward. Imposing a restriction on output is therefore key to identify supply noise shocks.

5 SVAR Analysis

In this section, we describe the data sources and provide additional results regarding the empirical analysis.

5.1 Methodology

The SVAR estimation strategy is based on a the estimation by OLS of the canonical VAR(p) model which can be written as

$$Y_t = \Phi\left(L\right) Y_t + v_t, \tag{A48}$$

where $Y_t = (Y_{1,t}, ..., Y_{n,t})'$ is an $(n \times 1)$ vector of endogenous variables, L is the lag operator,Φ is the $(n \times 1)$ matrix of estimated parameters, v_t is an $(n \times 1)$ vector of reduced-form estimated residuals such that $v_t \sim \text{iid}(0, \Sigma)$, with Σ, a symmetric positive definite matrix. Canonical innovations, v_t, are related to structural innovations, ξ_t, by the following linear combination $v_t = \Gamma \xi_t$, where structural shocks are by assumption orthogonalized, such that $\xi_t \sim \text{iid}(0, \mathrm{I}_{n\times n})$ and Γ is a $(n \times n)$ non singular matrix. Our methodology requires to express the MA(∞) representation of the VAR(p) model $Y_t = \sum_{i=0}^{\infty} r_i \xi_{t-i}$, where $r_i = \partial Y_{t+i} / \partial \xi'_t$ is interpreted as IRF of the system, Y_{t+i}, to a variation of ξ_t , $\forall i \geq 0$. The estimated IRFs are asymptotically normal (Lutkepohl, 2005). Following the Monte Carlo strategy suggested by Hamilton (1995), we randomly generate a set of coefficients $\hat{\Phi}\left(L\right)$ drawn from the normal distribution of the estimated reduced-form parameters and a matrix $\hat{\Sigma}$ drawn from the asymptotic distribution of the variance-covariance matrix of the reduced-form residuals associated to the canonical VAR (A48) since Σ can be re-written as $\Sigma = \tilde{\Gamma} Q Q' \tilde{\Gamma}'$, where $\tilde{\Gamma}$ is a Choleski decomposition of Σ and Q is an orthonormal matrix (i.e. $QQ' = \mathrm{I}_{n \times n}$). Therefore, there is an infinite number of possible combinations in Q and therefore structural shocks are identified by drawing randomly Q and imposing identifying restriction on the impulse response functions (IRFs) of selected variables to shocks.

The algorithm to select the successful draws follows Arias et al. (2018):

1. Draw Φ from a multivariate normal distribution $\mathcal{N}(\hat{\Phi}, \hat{\Sigma}_{\Phi})$ and independently Σ from a multivariate normal distribution $\mathcal{N}(\hat{\Sigma}, \hat{\Sigma}_{\Sigma})$ where $\hat{\Sigma}_{\Phi}$ and $\hat{\Sigma}_{\Sigma}$ are matrices of variance covariance of $\hat{\Phi}$ and $\hat{\Sigma}$, respectively.

2. Computes the IRFs $\{r_j\}_{j=0}^{50}$ and the long-run IRFs as the cumulated sum of $\{r_j\}_{j=0}^{50}$.

3. From the set of parameters satisfying the zero restrictions, draw a rotation matrix, Q, independently from a normal distribution $\mathcal{N}(0, 1)$.

4. Keep $\{r_j\}_{j=0}^{50} = f^{-1}(\Phi, \Sigma, Q)$ if the sign restrictions are satisfied.

5. Return to step 1 until the maximum number of draws is reached.

Importantly, Arias et al. (2018) estimate a BVAR canonical model while we adopt a parametrized OLS estimation strategy. Our methodology is identical to them when they impose uniform prior distribution on parameters.

5.2 Data Description

The series used in the baseline SVAR model are given by

$$Y_t = [\Delta y_t,\ \pi_t,\ \mathrm{E}_t\{\Delta y_t\} - \Delta \tilde{y}_t,\ \mathrm{E}_t\{\pi_t\} - \tilde{\pi}_t], \tag{A49}$$

where we detail here their sources and transformation.

♦ Δy_t: real GNP/GDP. Unit of Measurement: Q/Q Growth, annual Rate, %. *Source*: Federal Reserve Economic Data. Real GNP (Id: GNPC96) prior to 1992; Real GDP 1992 to present (Id: GDPC1). Billions of real dollars. Seasonally adjusted. Annual rate.

♦ $\mathrm{E}_t\{\Delta y_t\}$: Nowcast on Real GNP/GDP. Unit of Measurement: % change of median response, annualized rate. *Source* : Survey of Professional Forecaster, Federal Reserve Bank of Philadelphia (Id: RGDP). Real GNP prior to 1992. Real GDP 1992-present.

♦ $\Delta \tilde{y}_t$: Actual real GNP/GDP first release. Unit of Measurement: Q/Q Growth, annual Rate, %. *Source*: Real-Time Data Research Center, Federal Reserve Bank of Philadelphia (Id: ROUTPUT).

♦ π_t: Implicit GDP price deflator. Unit of Measurement: Q/Q Growth, annual Rate, %. *Source*: Federal Reserve Economic Data (Id: GDPDEF).

♦ $\mathrm{E}_t\{\pi_t\}$: Nowcast about GNP deflator prior to 1992. GDP deflator 1992-1995. Chain-weighted price index for GDP 1996-present. Unit of Measurement: % change of median response, annualized rate. *Source* : Survey of Professional Forecaster, Federal Reserve Bank of

Philadelphia (Id: PGDP).

⧫ $\tilde{\pi}_t$: Actual Price Index for GNP/GDP first release. Unit of Measurement: Q/Q Growth, annual Rate, %. *Source*: Real-Time Data Research Center, Federal Reserve Bank of Philadelphia (Id: P).

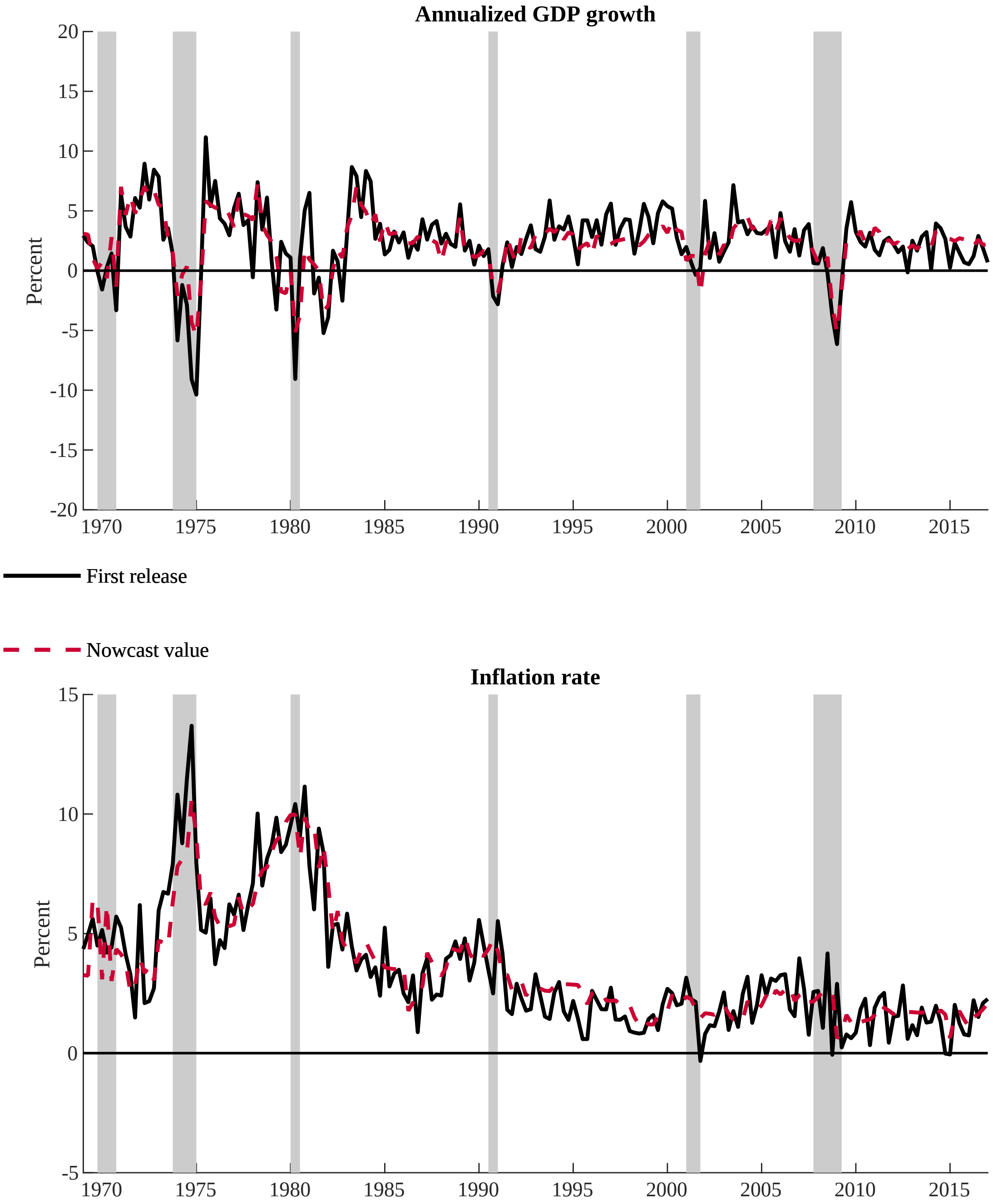
In Figure A2, we show the data used for estimation, focusing on the first release of real GDP growth and the inflation rate (solid lines, $\Delta\tilde{y}_t$ and $\tilde{\pi}_t$, resp.) and the corresponding median nowcast prediction (dashed lines, $\mathrm{E}_t\left\{\Delta y_t\right\}$ and $\mathrm{E}_t\left\{\pi_t\right\}$, resp.). The nowcast error used in the SVAR estimation is therefore the difference between the dashed and the solid line for GDP growth (upper panel) and inflation rate (lower panel). The figure shows that agents make systematic mistakes in their nowcasts, in particular for inflation since nowcast *errors* are significantly different from zero over the all sample. Notice that a nowcast prediction coincides with the median forecast of the variable within the quarter. The questionnaire is sent at the end of the first month of the quarter and the deadline to submit it is in the middle of the second month of the quarter. At the time of the forecast, the information set of the forecasters consists of data until the previous quarter (included).

5.3 First and Final Release

In the baseline analysis, we measure the nowcast errors of GDP growth and the inflation rate as the difference between the median nowcast prediction of a variable and its associated first-release observation. Figure A3 compares the first-release (solid lines) and the most recent-release (dashed lines) observations of the annualized real GDP growth (upper panel) and annualized GDP deflator inflation rate (lower panel). The correlation between first- and most recent-release is 80% for GDP growth and 93% for inflation, over the full sample.

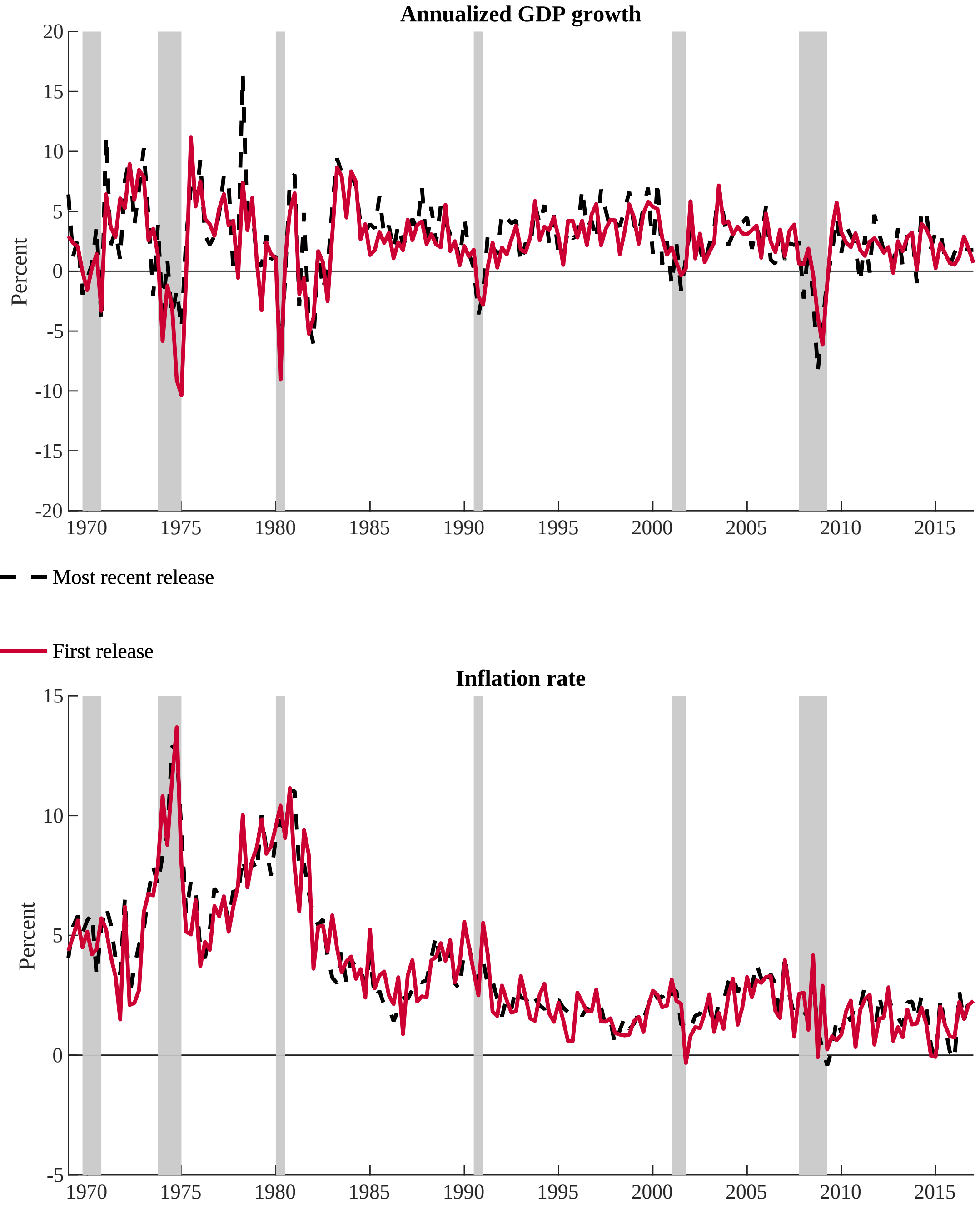
Table A7 displays the unconditional variance decomposition of output growth and inflation and their associated nowcast errors when nowcast errors are measured as the difference between the nowcast prediction and the first-, second-, third- and most recent-release observation of the variable. We find that the contribution of supply noise to output and inflation is the most impacted by data revisions. In particular, when we use the most-recent release in the measure of nowcast errors, noise shocks contributions in a similar amount to GDP growth volatility but the repartition of the two shocks is affected, compared to the benchmark model. When it comes to the nowcast errors, the the results are quite simular to the baseline estimation. We complement these results with Figure A4 which displays the IRFs of output and inflation and their associated nowcast errors to the four shocks for several measures of nowcast errors depending on the release horizon. The solid lines corresponds to nowcast errors computed as the difference between the nowcast prediction and the first release (benchmark estimation). The dashed line corresponds to a second-release based measure. The dotted line corresponds to the thrid-release based measure. The dashed-dotted line corresponds to the most recent-release based measure. The IRFs which are the most affected by the measure are those computed on the most-recent release observation. This is not surprising as most-recent release (or final-release) series incorporate changes in national account methodology.

Figure A2: First-release observations and nowcasts predictions



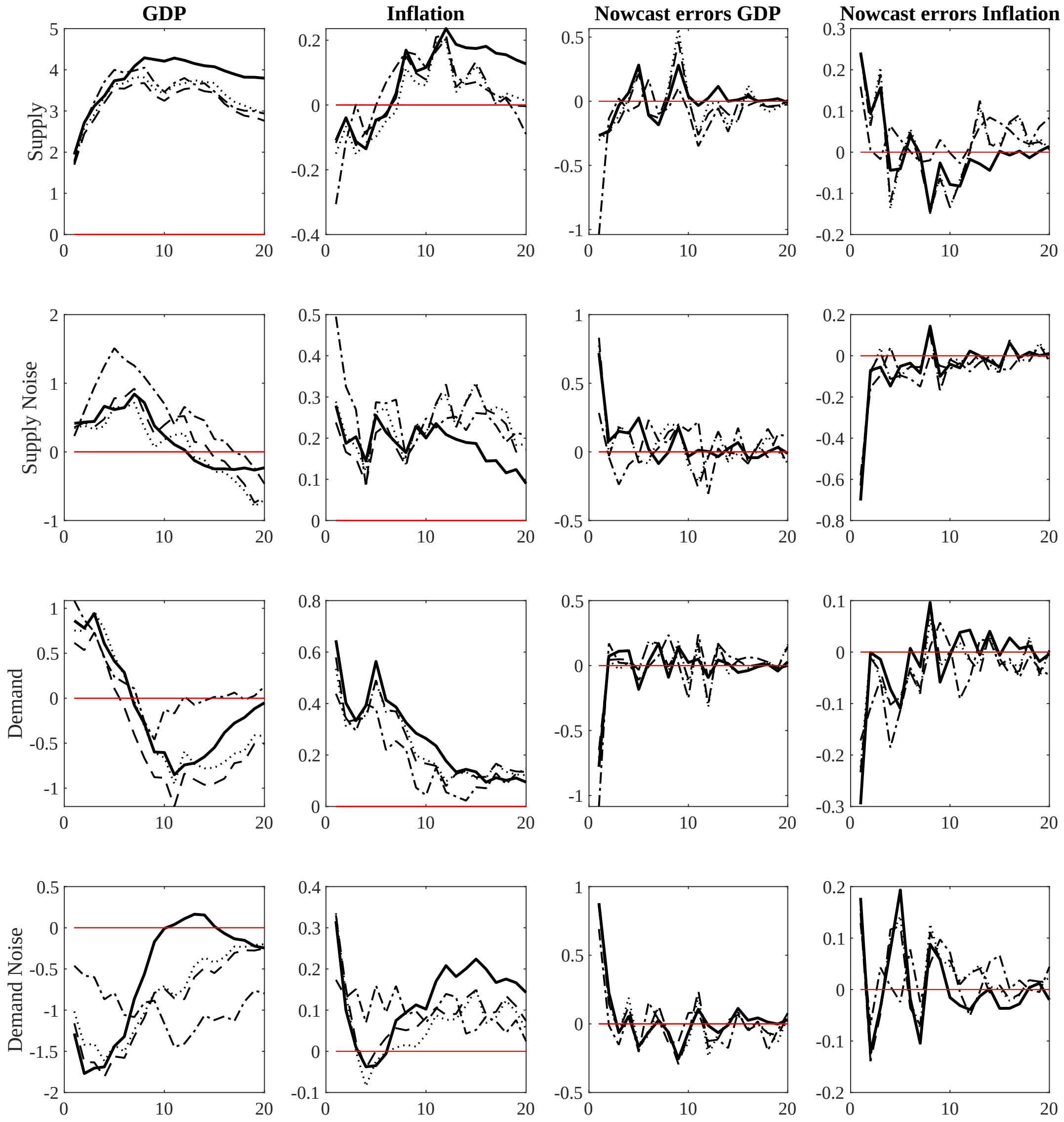
Note: The solid line is the first release of the annualized real GDP growth rate ($\Delta\tilde{y}_t$, upper panel) and GDP deflator inflation rate ($\tilde{\pi}_t$, lower panel). The first release series are obtained from the Real-Time Data Set of the Federal Reserve Bank of Philadelphia. The dash line is the annualized percentage change of the median response of the nowcast prediction for real GDP ($\mathrm{E}_t\left\{\Delta y_t\right\}$, upper panel) and GDP deflator ($\mathrm{E}_t\left\{\pi_t\right\}$, lower panel). The nowcast data are from the SPF of the Fed of Philadelphia.

Figure A3: First- and most-recent release observations



Note: The solid line is the first release observation of the variable. The dashed line is the most-recent release observation. The upper panel displays observations on the annualized real GDP growth rate. The lower panel displays observations on the annualized GDP deflator inflation rate. All series are obtained from the Real-Time Data Set of the Federal Reserve Bank of Philadelphia.

Figure A4: Impulse response functions with several release horizons



Note: The SVAR model is estimated with different measures of nowacast errros for GDP growth and inflation. Nowcast errors are computed as the difference between the nowcast predition and the first-release observation (solid lines), second-release observation (dashed lines), third-release observation (dotted lines), most recent-release observation (dash-dotted line).

Table A7. Unconditional variance decomposition for several release horizons

	Supply	Supply noise	Demand	Demand noise
Output Growth				
(a) Benchmark	0.44 [0.31,0.58]	0.09 [0.05,0.15]	0.17 [0.09,0.30]	0.24 [0.11,0.40]
(b) Second-release	0.39 [0.24,0.54]	0.14 [0.09,0.22]	0.19 [0.12,0.29]	0.22 [0.11,0.39]
(c) Third-release	0.42 [0.25,0.57]	0.13 [0.08,0.20]	0.19 [0.12,0.31]	0.19 [0.10,0.38]
(d) Most recent-release	0.49 [0.37,0.58]	0.14 [0.09,0.20]	0.21 [0.15,0.29]	0.15 [0.09,0.24]
Inflation rate				
(a) Benchmark	0.17 [0.07,0.39]	0.18 [0.04,0.42]	0.37 [0.17,0.60]	0.14 [0.07,0.31]
(b) Second-release	0.16 [0.8,0.36]	0.27 [0.08,0.50]	0.34 [0.16,0.55]	0.11 [0.4,0.23]
(c) Third-release	0.15 [0.07,0.32]	0.31 [0.12,0.53]	0.33 [0.16,0.55]	0.11 [0.05,0.22]
(d) Most recent-release	0.16 [0.09,0.30]	0.39 [0.20,0.59]	0.26 [0.12,0.45]	0.10 [0.04,0.20]
Output growth nowcast errors				
(a) Benchmark	0.15 [0.10,0.23]	0.22 [0.13,0.34]	0.25 [0.12,0.46]	0.30 [0.13,0.51]
(b) Second-release	0.21 [0.14,0.29]	0.25 [0.18,0.34]	0.22 [0.15,0.35]	0.28 [0.16,0.41]
(c) Third-release	0.23 [0.16,0.12]	0.22 [0.15,0.32]	0.23 [0.16,0.55]	0.28 [0.15,0.42]
(d) Most recent-release	0.29 [0.20,0.39]	0.16 [0.11,0.21]	0.30 [0.18,0.43]	0.20 [0.10,0.39]
Inflation nowcast errors				
(a) Benchmark	0.16 [0.09,0.28]	0.46 [0.27,0.62]	0.15 [0.07,0.33]	0.15 [0.09,0.23]
(b) Second-release	0.24 [0.16,0.35]	0.40 [0.26,0.52]	0.16 [0.9,0.28]	0.16 [0.11,0.23]
(c) Third-release	0.24 [0.16,0.35]	0.40 [0.26,0.54]	0.15 [0.08,0.28]	0.16 [0.11,0.23]
(d) Most recent-release	0.14 [0.09,0.24]	0.49 [0.33,0.60]	0.18 [0.12,0.28]	0.14 [0.09,0.21]

Note: For each successful draw, the unconditional variance decomposition is computed. The upper number reports the median value and numbers under brackets are the 16th and 84th percentile values of the variance decomposition distribution.

5.4 Variance Decomposition

Figure A5 diplays the variance decomposition of GDP (in level) and inflation at each horizon in the baseline estimated SVAR model. The variance decomposition is computed using the median IRF. The demand noise shock explain a large amount of GDP fluctuations over the short-run (about 20% after one year) and noise shocks explain in total 25% of GDP fluctuations at this horizon. By construction, fundamental supply shocks explain all GDP fluctuations over the long-run. Fundamental demand shocks are the main driver of inflation fluctuations over all horizons, while demand noise shocks explain about 4% after one year. As mentionned in the main text, we show in Figure A13 that the unconditional variance decomposition is similar to the baseline model when we abstract from long-run identification restrictions and impose sign restrictions only.

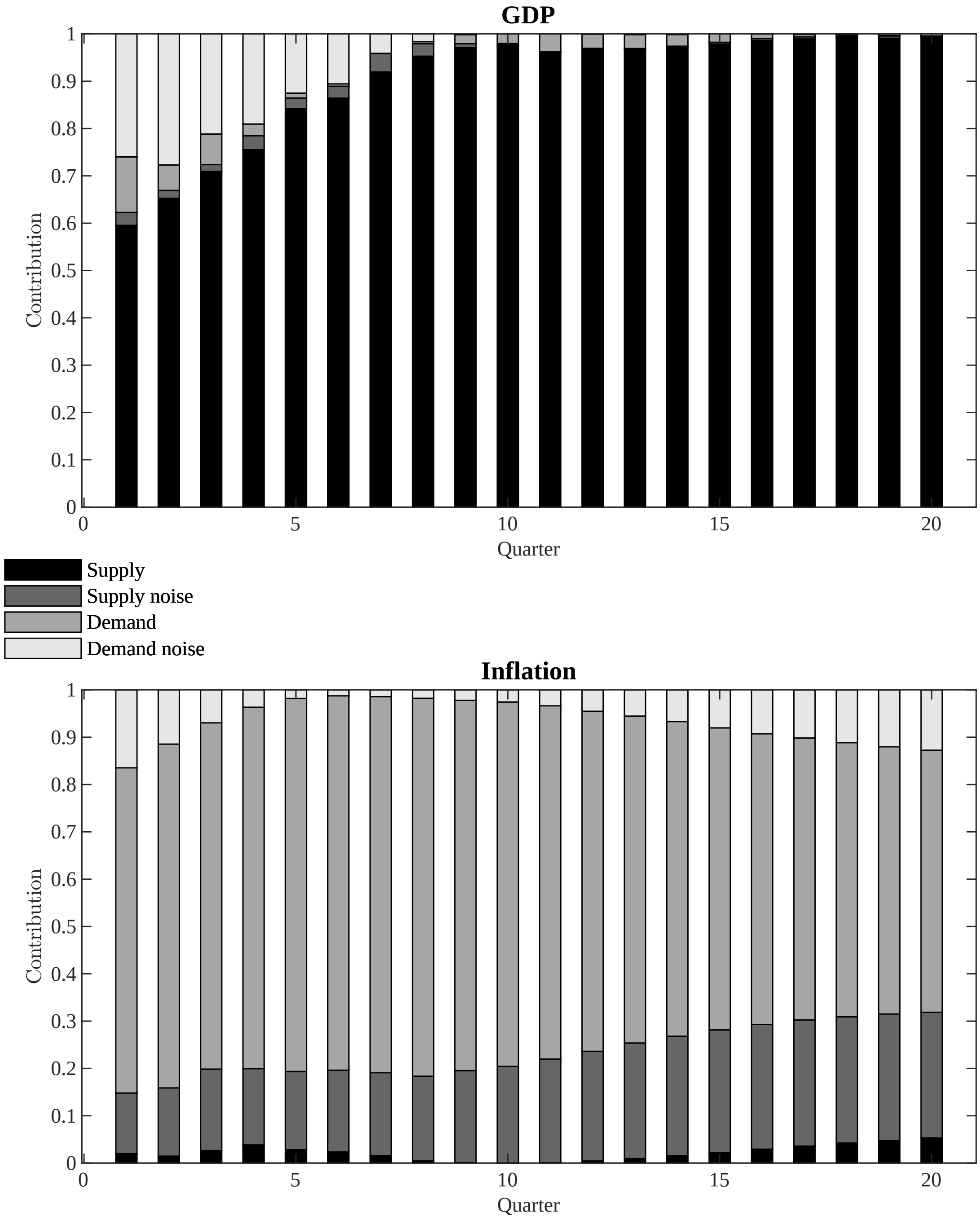
5.5 Monte Carlo Exercise

Figure A6 shows the model-based IRFs computed from the New Keynesian model estimated as in Section 3 and the SVAR-based IRFs from the baseline estimation as well as the 16th and 84th percentile region. The figure shows that the estimated theoretical model replicates quite well the empirical IRFs as most of the moments are inside the confidence interval. In particular, the model is able to replicate the magnitude of the reponses of nowcast errors. We then estimate the baseline SVAR model on artificial data generated from the theoretical model described in Section 1. The model is calibrated as described in Section 4.2 and Tables 4-5 of the paper. We then generate 100 artificial series of sample size $T = 300$, where the structural shocks ϵ_t^a, e_t^a, ϵ_t^b, e_t^b, are drawn from a i.i.d Normal distribution with zero mean and unitary variance. We then re-estimated the benchmark SVAR model over the 100 artificial data and compare the SVAR-based IRFs with the "true" IRFs generated from the Data Generating Process. Figure A7 displays the DGP-based and estimated IRFs of output, inflation and their associated nowcast errors to the four shocks. The SVAR model globally performs relatively well in reproducing the true IRFs. It cannot replicate the shape of the response of inflation to fundamental shocks. It is worth noting that it does not overestimate the responses of nowcasts errors to shocks. This means that our methodology does not artificially generate high conditional volatilities of errors, which will be key to assess the extent of information.

5.6 Robustness Checks

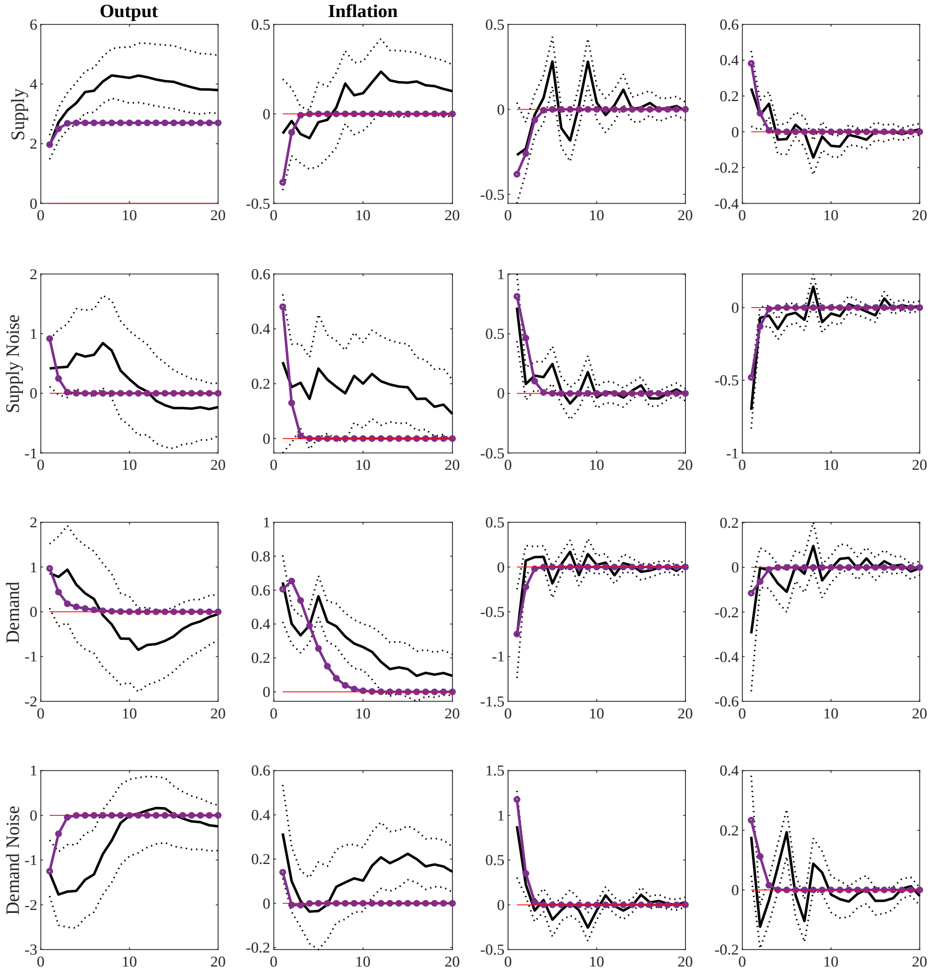
In this section, we provide the IRFs and the unconditional variance decomposition of variables for each robustness exercise presented in Section 4 of the manuscript. Table A8 reminds the sign and long-term identification restrictions imposed in the baseline estimation. Table A9 describes specifications for each robustness exercise. We then show in Figures A8 to A10 the IRFs associated to each Panel (a) to (j).

Figure A5: Conditional variance decomposition of real GDP and inflation.



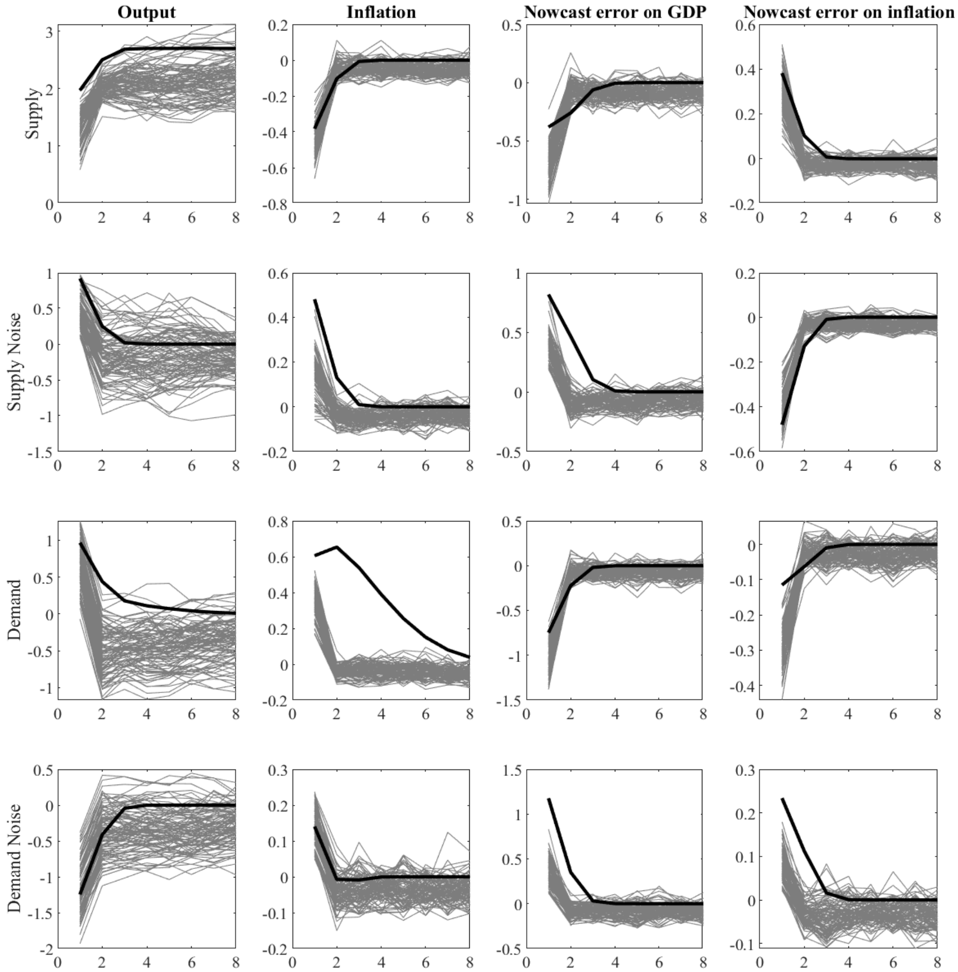
Note: The upper panel shows the variance decomposition of real GDP over several horizons. The lower panel displays the variance decomposition of inflation. The variance decomposition of variable i for shock j at horizon h is computed as $\Xi_{ijh} = r_{ijh}^2 \;/\; \left[\sum_{j=1}^{4} r_{ijh}^2\right]$, where r_{ijh} is the median IRF of variable i for shock j at horizon h.

Figure A6: Model-based and SVAR-based IRFs



Note: The black line corresponds to the median SVAR-based IRFs, the upper and lower dotted lines indicate the 16th and 24th percentile region. The dotted line corresponds to the model-based IRFs.

Figure A7: Monte Carlo Exercise



Note: The black line corresponds to the DGP-based IRF computed from the estimated New Keynesian model. The grey lines are the median IRFs computed from the SVAR estimated on each artificial data.

Table A8. Baseline Identification Restrictions.

	y_t	π_t	$E_t(\Delta y_t) - \tilde{y}_t$	$E_t(\pi_t) - \tilde{\pi}_t$
Supply (ϵ_t^a)	> 0 permanently	×	×	×
Supply noise (e_t^a)	> 0	×	> 0	< 0
Demand (ϵ_t^b)	×	> 0	< 0	< 0
Demand noise (e_t^b)	×	> 0	> 0	> 0

Note: The response of GDP is constructed by taking the sum of the cumulated response of GDP growth. Crosses correspond to unrestricted signs. Signs are imposed on the impact response of the variable to shocks. A cross corresponds to an unrestricted sign.

Table A9. Robustness Exercises.

Case	Title	Description
(a)	Benchmark	Baseline identification restrictions, see Table 1
(b)	Relax supply noise	Relax the sign of the response of output to the supply noise shock
(c)	Relax demand noise	Relax the sign of the response of inflation to the demand noise shock
(d)	Sign restrictions only	No-long-run restriction: $\frac{\partial y_t}{\partial \epsilon_t^a} > 0$; $\frac{\partial [E_t(y_t) - y_t]}{\partial \epsilon_t^a} < 0$;$\frac{\partial [E_t(\pi_t) - \pi_t]}{\partial \epsilon_t^a} > 0$;
(e)	Great Moderation	Baseline estimation over the sample 1983q2-2007q2
(f)	12 Lags	Baseline estimation over 12 lags
(g)	Third Release	Nowcast errors computed as $E_t\left\{\Delta y_t\right\} - \Delta y_t^{3^{rd}\text{release}}$ and $E_t\left\{\pi_t\right\} - \pi_t^{3^{rd}\text{release}}$
(h)	Mean Nowcast	Nowcast errors computed using $E_t\left\{x_t\right\}$ as the mean nowcast prediction
(i)	Three-variables SVAR	Drop $E_t\left\{\pi_t\right\} - \tilde{\pi}_t$ from the set of observables, baseline identification strategy

5.6.1 Impulse Response Functions

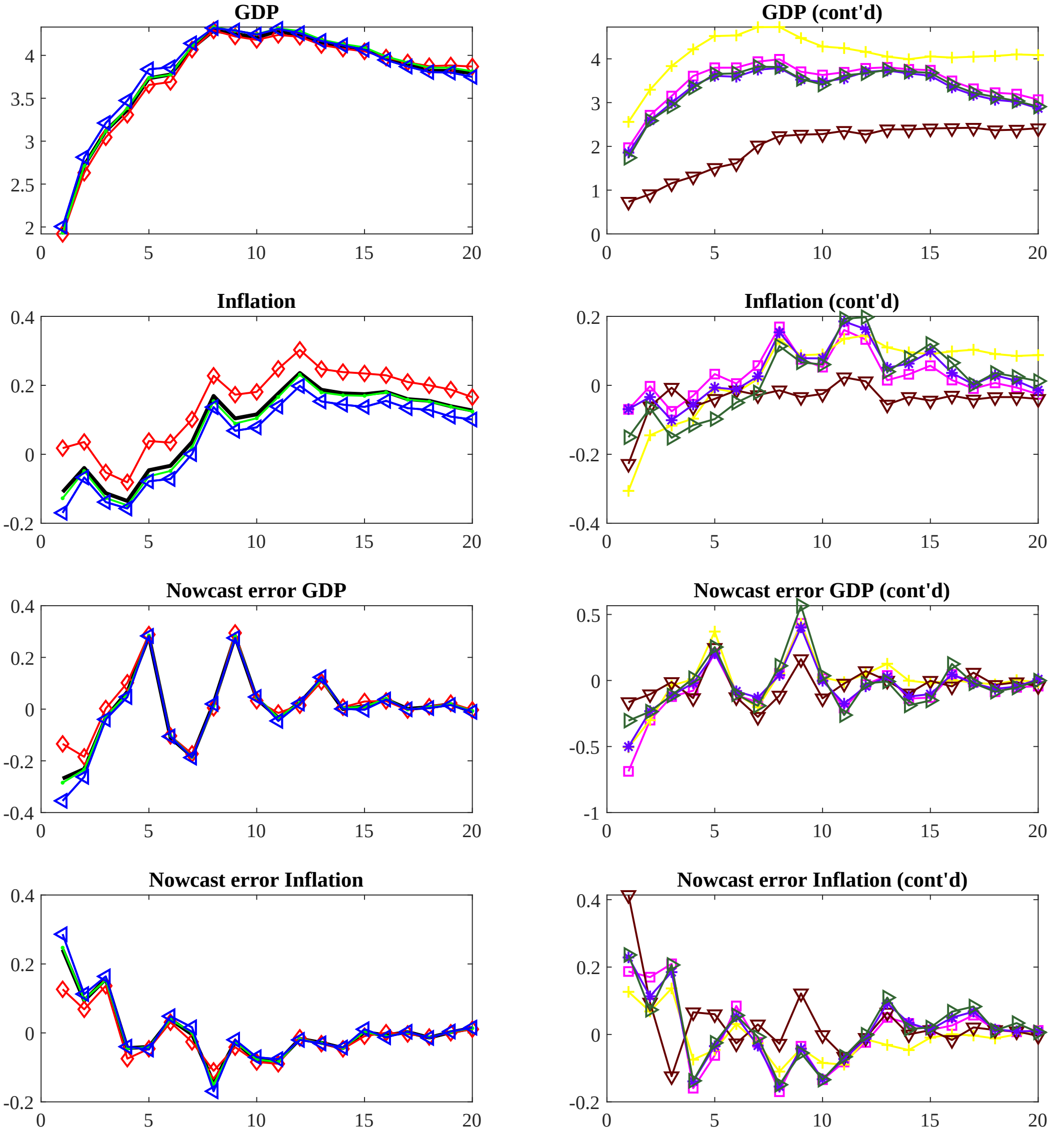
Figures A8 to A11 display the median IRfs of output, the inflation rate and their associated nowcast errors to fundamental supply shocks, fundamental demand shock, supply noise shocks and demand noise shocks respectively under specifications described in Table A9. These figures show that most of the IRFs are close to the baseline estimated IRFs. One of our main result that demand noise shocks are recessionary is valid under all robustness exercises (see Figure A11), although its magnitude is lower over the Great Moderation period. We rationalize this results in the main text with the monetary policy channel (see Section 4.3 in the paper). Figure **??** also shows that supply noise shocks are always inflationary except over the Great Moderation period.

Figure A12 complements Figures A8 to A11 since it reports the median IRFs of GDP as well as the 16th and 84th percentile region to the four shocks under specifications *a* to *d* in Table A9. This figure allows us to check whether the response of GDP is significant for all identification strategies. The last line of Figure A12 shows that the demand noise shock is always significantly recessionary as mentioned in the text. The second line shows that the response of output to supply noise shock is not significant when we adopt a identification strategy with unrestricted sign on output (*b* in Table A9). This suggests that restrictions on nowcast errors are not sufficient to disentangle nowcast errors are not sufficient to disentangle supply noise and transitory supply shocks.

5.6.2 Variance Decomposition

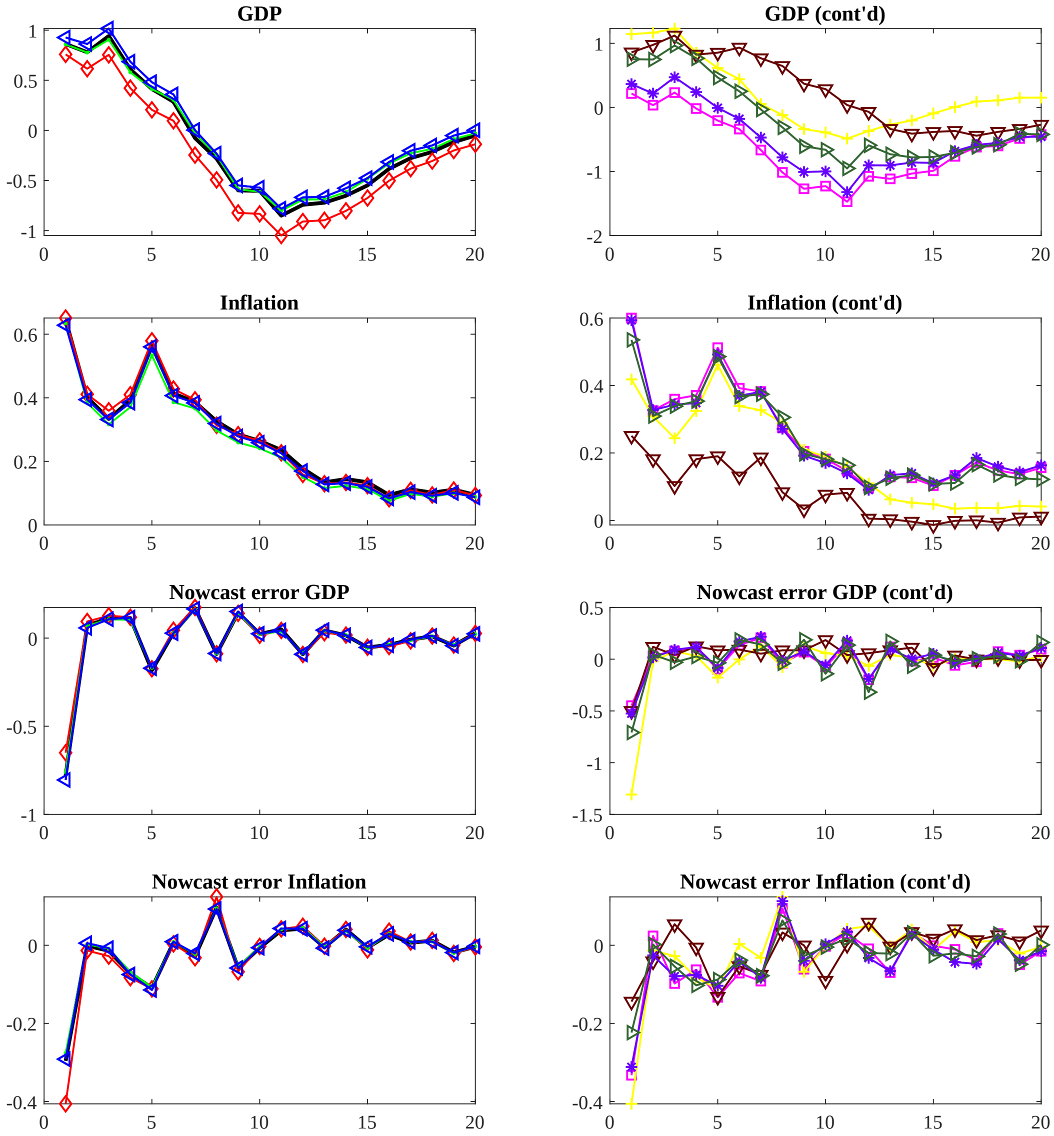
Tables A10 and A11 provide the unconditional variance decomposition of inflation, nowcast errors on output and inflation for each robustness exercise described in Table A9. They complement Table 3 in the main paper. We compute the unconditional variance decomposition of inflation for each successful draw so as to build a distribution of shocks' contributions to this variable.Each table displays the median of the unconditional variance decomposition as well as the 16% and 84% quantiles values under brackets. Table A10 shows that the variance decomposition of inflation is robust to all specifications, in particular, fundamental demand shocks explain a large part of inflation fluctuations. In the case of a SVAR abstracting from nowcast errors inflation, noise supply shock explain most of inflation fluctuations. Table A11 shows that the four shocks contributes by a similar amount to GDP nowcast fluctuations, which, as explained in the text, suggests the presence of private information among agents of the economy. Figure A13 complements Figure A5 by diplaying the variance decomposition of GDP (in level) and inflation at each horizon when the SVAR model is restricted through sign restrictions only (case *d* in Table Table A9). Comparing Figures A5 and A13, we find that the long- and short-run variance decomposition does not depend on the long-run restrictions. This reinforces the validity of our results.

Figure A8: IRFs to a fundamental supply shock.



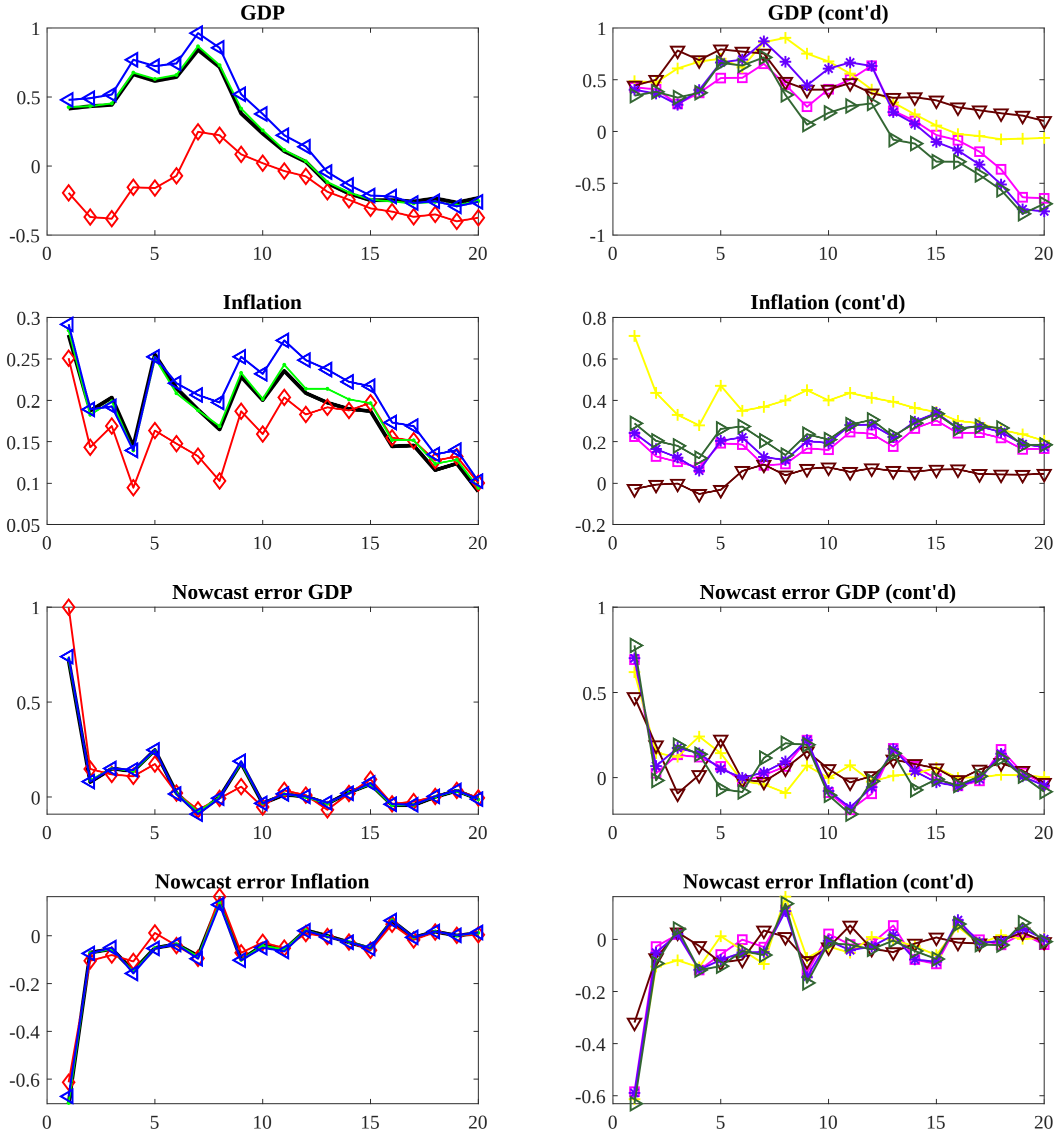
Note: On the left panel, the solid (black) line corresponds to the "baseline" case (a in Table A9). The (red) line with diamond markers corresponds to the "relax supply noise" case (b in Table A9). The (green) line with dot markers corresponds to the "relax demand noise" case (c in Table A9). The (blue) line with lower-than symbol marker corresponds to the "sign restrictions only" case (d in Table A9). On the right panel, the (brown) line with lower triangular markers corresponds to the "great moderation" case (e in Table A9). The (purple) line with stars markers corresponds to the "12 lags" case (f in Table A9). The (green) line with superior markers corresponds to the "third release" case (g in Table A9). The (magenta) line with square markers corresponds to the "mean nowcast" case (h in Table A9). The (yellow) line with lower-than symbol markers corresponds to the "three variables SVAR" case (i in Table A9)

Figure A9: IRFs to a fundamental demand shock.



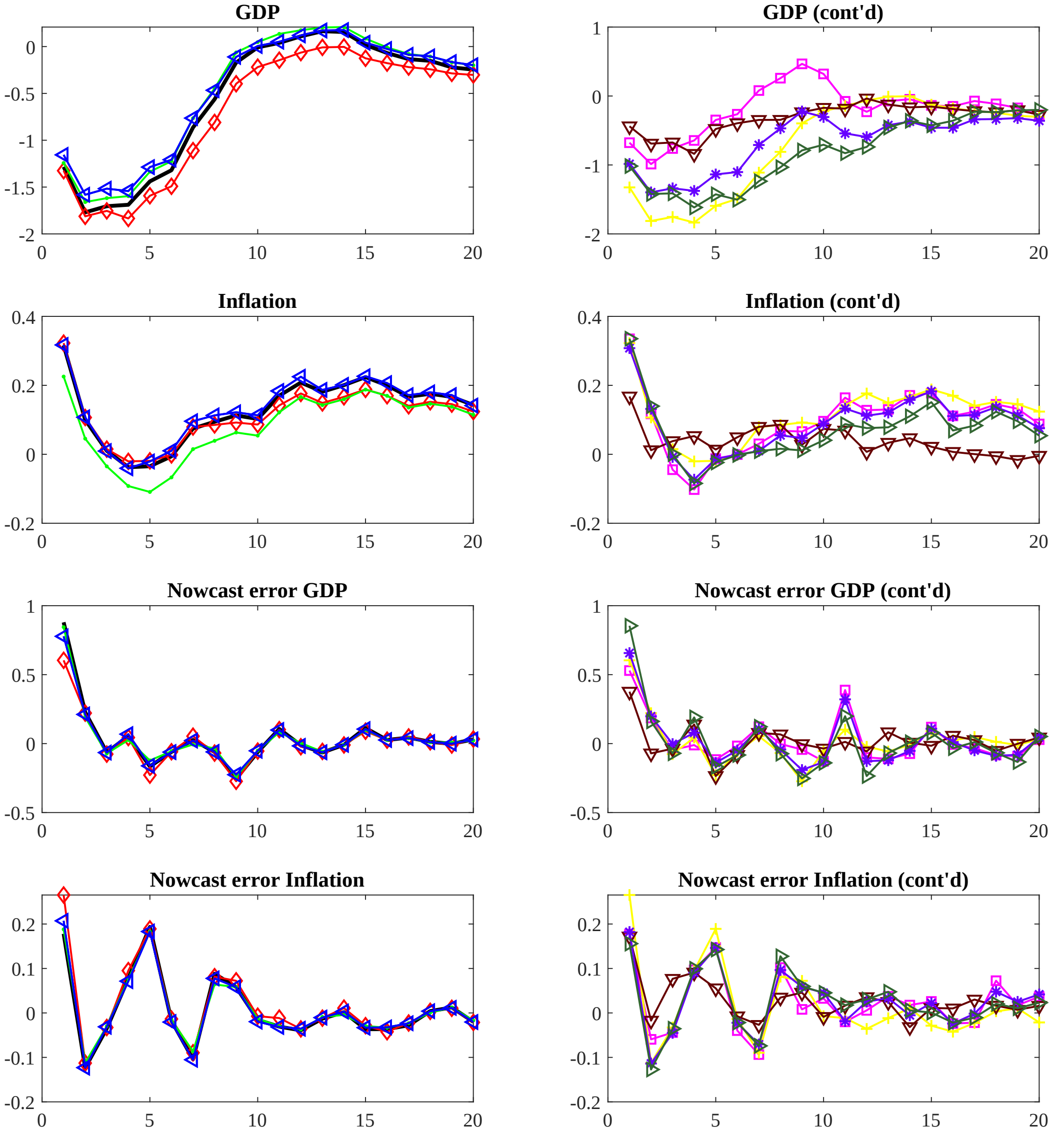
Note: On the left panel, the solid (black) line corresponds to the "baseline" case (*a* in Table A9). The (red) line with diamond markers corresponds to the "relax supply noise" case (*b* in Table A9). The (green) line with dot markers corresponds to the "relax demand noise" case (*c* in Table A9). The (blue) line with lower-than symbol marker corresponds to the "sign restrictions only" case (*d* in Table A9). On the right panel, the (brown) line with lower triangular markers corresponds to the "great moderation" case (*e* in Table A9). The (purple) line with stars markers corresponds to the "12 lags" case (*f* in Table A9). The (green) line with superior markers corresponds to the "third release" case (*g* in Table A9). The (magenta) line with square markers corresponds to the "mean nowcast" case (*h* in Table A9). The (yellow) line with lower-than symbol markers corresponds to the "three variables SVAR" case (*i* in Table A9)

Figure A10: IRFs to a supply-noise shock.



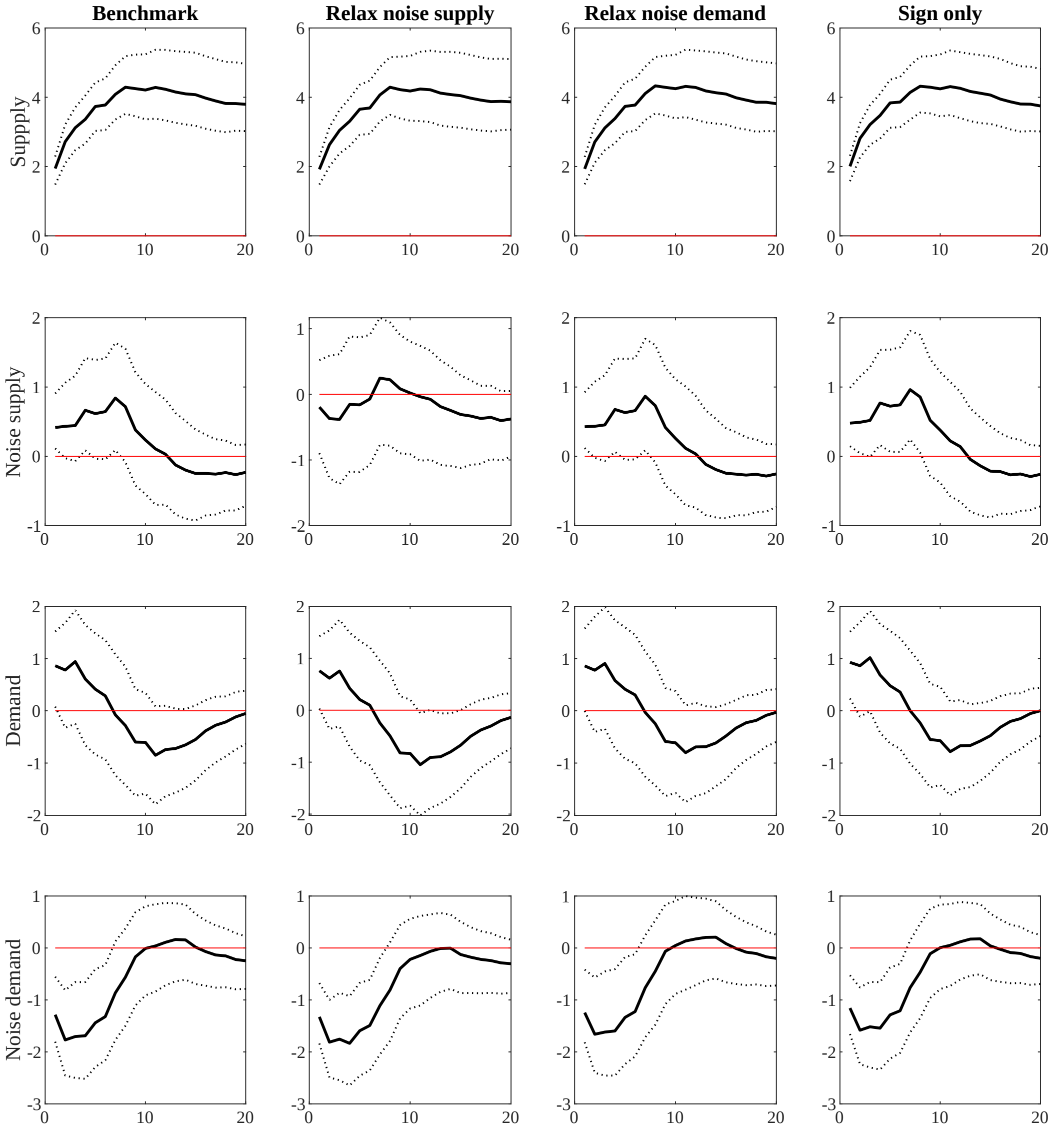
Note: On the left panel, the solid (black) line corresponds to the "baseline" case (*a* in Table A9). The (red) line with diamond markers corresponds to the "relax supply noise" case (*b* in Table A9). The (green) line with dot markers corresponds to the "relax demand noise" case (*c* in Table A9). The (blue) line with lower-than symbol marker corresponds to the "sign restrictions only" case (*d* in Table A9). On the right panel, the (brown) line with lower triangular markers corresponds to the "great moderation" case (*e* in Table A9). The (purple) line with stars markers corresponds to the "12 lags" case (*f* in Table A9). The (green) line with superior markers corresponds to the "third release" case (*g* in Table A9). The (magenta) line with square markers corresponds to the "mean nowcast" case (*h* in Table A9). The (yellow) line with lower-than symbol markers corresponds to the "three variables SVAR" case (*i* in Table A9).

Figure A11: IRFs to a demand-noise shock.



Note: On the left panel, the solid (black) line corresponds to the "baseline" case (a in Table A9). The (red) line with diamond markers corresponds to the "relax supply noise" case (b in Table A9). The (green) line with dot markers corresponds to the "relax demand noise" case (c in Table A9). The (blue) line with lower-than symbol marker corresponds to the "sign restrictions only" case (d in Table A9). On the right panel, the (brown) line with lower triangular markers corresponds to the "great moderation" case (e in Table A9). The (purple) line with stars markers corresponds to the "12 lags" case (f in Table A9). The (green) line with superior markers corresponds to the "third release" case (g in Table A9). The (magenta) line with square markers corresponds to the "mean nowcast" case (h in Table A9). The (yellow) line with lower-than symbol markers corresponds to the "three variables SVAR" case (i in Table A9)

Figure A12: GDP reponse to shocks under several identification strategy.



Note: In each subplot is reported the median IRFs of GDP to shock (shown in y-axis) under several identification strategies as well as the 16th and 84th percentile region. The first vertical panel shows the responses of GDP in the baseline SVAR estimation (a in Table A9). The second vertical panel reports the responses of output in the "relax supply noise" case (b in Table A9). The third vertical panel reports the output response in the "relax demand noise" case (c in Table A9). The fourth vertical panel reports the response of output in the "sign restrictions only" case (d in Table A9).

Table A10. Robustness: Unconditional variance decomposition

	Supply	Supply noise	Demand	Demand noise
Inflation				
(a) Benchmark	0.17 [0.07,0.39]	0.18 [0.04,0.42]	0.37 [0.17,0.60]	0.14 [0.07,0.31]
(b) Relax supply noise	0.15 [0.07,0.30]	0.24 [0.09,0.47]	0.34 [0.16,0.57]	0.15 [0.07,0.31]
(c) Relax demand noise	0.17 [0.07,0.36]	0.17 [0.05,0.41]	0.34 [0.14,0.59]	0.15 [0.06,0.37]
(d) Sign restrictions only	0.15 [0.8,0.29]	0.21 [0.5,0.45]	0.37 [0.17,0.60]	0.16 [0.07,0.32]
(e) Great Moderation	0.22 [0.12,0.40]	0.18 [0.9,0.32]	0.34 [0.18,0.52]	0.16 [0.8,0.29]
(f) 12 Lags	0.15 [0.7,0.34]	0.25 [0.09,0.49]	0.34 [0.19,0.57]	0.12 [0.05,0.24]
(g) Third Release	0.15 [0.07,0.32]	0.31 [0.12,0.53]	0.33 [0.16,0.55]	0.11 [0.05,0.22]
(h) Mean Nowcast	0.15 [0.06,0.34]	0.21 [0.08,0.44]	0.39 [0.21,0.60]	0.13 [0.06,0.25]
(i) Three-variables SVAR	0.13 [0.06,0.25]	0.61 [0.31,0.79]	0.21 [0.08,0.52]	–

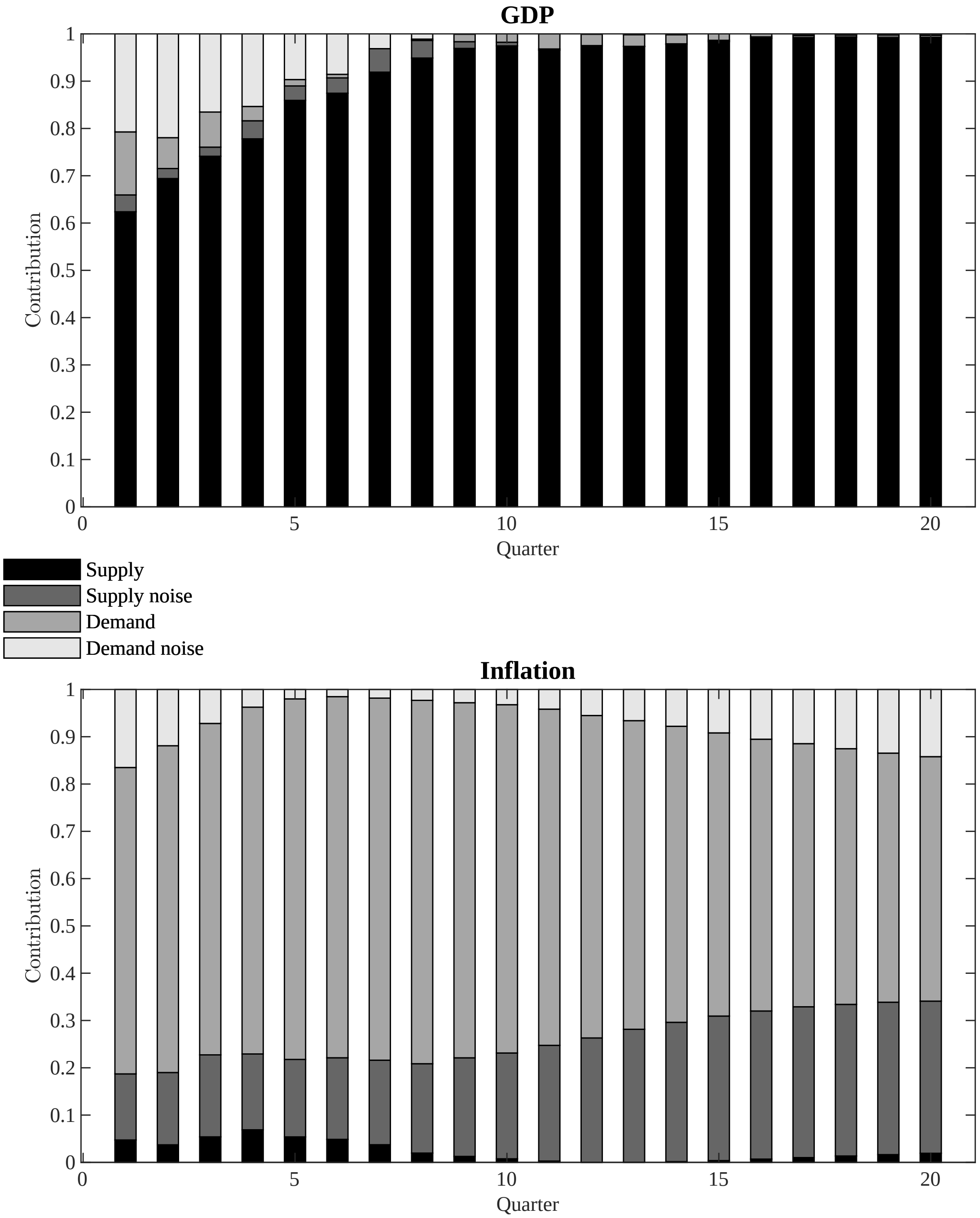
Note: For each successful draw, the unconditional variance decomposition is computed. The upper number reports the median value and numbers under brackets are the 16th and 84th percentile values of the variance decomposition distribution.

Table A11. Robustness: Unconditional variance decomposition (continued)

	Supply	Supply noise	Demand	Demand noise
Output growth nowcast errors				
(a) Benchmark	0.15 [0.10,0.23]	0.22 [0.13,0.34]	0.25 [0.12,0.46]	0.30 [0.13,0.51]
(b) Relax supply noise	0.14 [0.09,0.21]	0.33 [0.18,0.52]	0.21 [0.11,0.42]	0.22 [0.11,0.41]
(c) Relax demand noise	0.16 [0.10,0.24]	0.22 [0.13,0.35]	0.24 [0.11,0.49]	0.28 [0.12,0.51]
(d) Sign restrictions only	0.17 [0.11,0.24]	0.23 [0.14,0.37]	0.26 [0.12,0.49]	0.26 [0.11,0.49]
(e) Great Moderation	0.25 [0.17,0.34]	0.25 [0.17,0.34]	0.26 [0.17,0.35]	0.21 [0.13,0.31]
(f) 12 Lags	0.23 [0.15,0.34]	0.24 [0.17,0.32]	0.21 [0.15,0.32]	0.26 [0.16,0.40]
(g) Third Release	0.23 [0.16,0.31]	0.22 [0.15,0.32]	0.23 [0.15,0.36]	0.28 [0.15,0.42]
(h) Mean Nowcast	0.30 [0.19,0.40]	0.24 [0.17,0.31]	0.20 [0.14,0.29]	0.23 [0.15,0.36]
(i) Three-variables SVAR	0.26 [0.18,0.35]	0.20 [0.10,0.40]	0.53 [0.30,0.67]	–
Inflation nowcast errors				
(a) Benchmark	0.16 [0.09,0.28]	0.46 [0.27,0.62]	0.15 [0.07,0.33]	0.15 [0.09,0.23]
(b) Relax supply noise	0.14 [0.09,0.24]	0.38 [0.20,0.58]	0.21 [0.09,0.44]	0.18 [0.11,0.30]
(c) Relax demand noise	0.16 [0.09,0.29]	0.46 [0.27,0.62]	0.15 [0.07,0.32]	0.15 [0.09,0.25]
(d) Sign restrictions only	0.18 [0.10,0.30]	0.44 [0.26,0.61]	0.15 [0.07,0.32]	0.15 [0.10,0.25]
(e) Great Moderation	0.36 [0.22,0.52]	0.24 [0.13,0.40]	0.17 [0.10,0.29]	0.16 [0.09,0.25]
(f) 12 Lags	0.23 [0.15,0.34]	0.36 [0.21,0.51]	0.19 [0.10,0.35]	0.16 [0.11,0.24]
(g) Third Release	0.24 [0.16,0.35]	0.40 [0.26,0.54]	0.15 [0.08,0.28]	0.16 [0.11,0.23]
(h) Mean Nowcast	0.24 [0.17,0.34]	0.34 [0.27,0.49]	0.21 [0.12,0.35]	0.16 [0.11,0.24]

Note: For each successful draw, the unconditional variance decomposition is computed. The upper number reports the median value and numbers under brackets are the 16th and 84th percentile values of the variance decomposition distribution.

Figure A13: Conditional variance decomposition: SVAR with Sign restrictions only



Note: The IRFs are computed from an estimated SVAR model identified through sign restrictions only (case d in Table Table A9). The upper panel shows the variance decomposition of real GDP over several horizons. The lower panel displays the variance decomposition of inflation. The variance decomposition of variable i for shock j at horizon h is computed as $\Xi_{ijh} = r_{ijh}^2 \ / \ \left[\sum_{j=1}^{4} r_{ijh}^2\right]$, where r_{ijh} is the median IRF of variable i for shock j at horizon h.

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