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The Transmission of Monetary Policy Shocks†

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Commonly used instruments for the identification of monetary policy disturbances are likely to combine the true policy shock with information about the state of the economy due to the information disclosed through the policy action. We show that this signaling effect of monetary policy can give rise to the empirical puzzles reported in the literature, and propose a new high-frequency instrument for monetary policy shocks that accounts for informational rigidities. We find that a monetary tightening is unequivocally contractionary, with deterioration of domestic demand, labor and credit market conditions as well as of asset prices and agents' expectations. (*JEL* D82, D84, E32, E43, E52, E58, G12)

A major recent advancement in the empirical literature on the transmission of monetary policy shocks has been the adoption of external instruments thought to provide direct measures of the structural policy disturbances, e.g., the narrative instrument proposed by Romer and Romer (2004) or the market surprises of Gürkaynak, Sack, and Swanson (2005) as used in Gertler and Karadi (2015). However, as documented in Coibion (2012) and in Ramey (2016), the estimated dynamic responses to monetary policy shocks can be sensitive to the choice of the instrument, sample, and empirical specification. In this paper, we propose an explanation for such instabilities that is based on models of imperfect information and

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propose an identification strategy that is robust to the presence of information frictions in the economy. We argue that accounting for such informational rigidities is crucial to understand some of the puzzles in the literature. Information asymmetries between the public and the central bank can in fact give rise to an "information channel" for monetary policy actions (see Romer and Romer 2000, Melosi 2017, Tang 2013): to informationally constrained agents, a policy rate hike can signal either a deviation of the central bank from its monetary policy rule—i.e., a contractionary monetary shock—or stronger than expected fundamentals to which the monetary authority endogenously responds. Empirical specifications that do not take into account information frictions, and that therefore do not disentangle these two scenarios, are likely to retrieve dynamic responses that confound the effects of a monetary policy shock with the endogenous response of the central bank to changes in the economy, leading to the well-known price and activity puzzles.

As observed in Blinder et al. (2008), imperfect and asymmetric information between the public and the central bank are the norm, not the exception, in monetary policy.[1] However, while this observation has informed many theoretical attempts to include informational imperfections in the modeling of monetary policy, it has been largely disregarded in the empirical identification of the shocks. Indeed, popular instruments for monetary policy shocks that are constructed in leading identification schemes can be thought of as assuming that either the central bank (e.g., Romer and Romer 2004) or market participants (e.g., Gertler and Karadi 2015) enjoy perfect information. Under these assumptions, controlling for the information set of the perfectly informed agent is sufficient to identify the shock. However, if all agents in the economy enjoyed full information, different instruments would deliver identical results. On the contrary, responses may diverge with dispersed information.

This paper provides evidence of the presence of information frictions that are relevant for monetary policy and discusses their implications for the identification of the shocks. We proceed in steps. In Section I, we show in a stylized model how imperfect information can invalidate commonly used instruments, and provide testable implications of the presence of information frictions. In Section II, we formally test for the presence of information frictions in leading instruments for monetary policy shocks and provide evidence in line with the predictions of our simple model. First, high-frequency instruments—a measure of the revision of market-based expectations that follows a monetary announcement—are predictable and autocorrelated (see also Ramey 2016). We interpret this as an indication of the sluggish adjustment of expectations, in line with what is documented for different types of economic agents using survey data.[2,3] This is the emerging feature of

[1] Our methodology builds on the insights provided by models of imperfect—noisy and sticky—information and asymmetric information (e.g., Woodford 2001, Mankiw and Reis 2002, Sims 2003, Mackowiak and Wiederholt 2009) and, empirically, combines insights from Romer and Romer's (2004) narrative identification and the high-frequency identification (HFI) of Gertler and Karadi (2015). Reviews on models of imperfect information and learning in monetary policy are in Mankiw and Reis (2010), Sims (2010), and Gaspar, Smets, and Vestin (2010).

[2] See, for example, Mankiw, Reis, and Wolfers (2004); Coibion and Gorodnichenko (2012, 2015); and Andrade and Le Bihan (2013).

[3] Looking at financial markets, Gourinchas and Tornell (2004); Piazzesi, Salomao, and Schneider (2015); Bacchetta, Mertens, and van Wincoop (2009); and Cieslak (2016) have connected systematic forecast errors in survey forecasts to puzzles in financial markets.

models of imperfect information. Second, high-frequency market-based surprises around policy announcements correlate with central banks' private macroeconomic forecasts (see also Barakchian and Crowe 2013, Gertler and Karadi 2015, Ramey 2016). We think of this as evidence of the signaling channel discussed in Melosi (2017)—i.e., the transfer of central banks' private information implicitly disclosed through policy actions and due to the information asymmetry between private agents and the central bank (Romer and Romer 2000). Finally, we show that narrative surprises, obtained with respect to the central bank's information set only (Romer and Romer 2004, Cloyne and Hürtgen 2016), are equally affected by informational frictions. Specifically, they are autocorrelated, predictable by past information, and may contain anticipated policy shifts—e.g., forward guidance announcements.

Taking stock of this evidence, in Section III, we define monetary policy shocks as exogenous shifts in the policy instrument that surprise market participants, are unforecastable, and are not due to the central bank's systematic response to its own assessment of the macroeconomic outlook. Accordingly, we construct an instrument for monetary policy shocks by projecting market-based monetary surprises on their own lags, and on the central bank's information set, as summarized by Greenbook forecasts.[4]

We use this informationally robust instrument to identify the shocks in an SVAR-IV (see Stock and Watson 2012, 2018; Mertens and Ravn 2013). We start by showing in Section IV that in a standardly specified monetary vector autoregression (VAR) such as, e.g., the one in Coibion (2012), and contrary to other leading instruments, our identification does not give rise to either output or price puzzles. We also show that the endogenous component in high-frequency monetary surprises—that is, due to the information channel—produces in the VAR responses that are compatible with the effects of aggregate demand shocks that the central bank is likely to respond to. In Section V, we then study the transmission of monetary policy shocks on a large and heterogeneous set of both macroeconomic and financial variables as well as on private sector forecasts and medium and long-term interest rates. We find that a monetary contraction is unequivocally and significantly recessionary. The contraction in output is sudden, significant, and larger than reported in previous studies. It is accompanied by a contraction in prices, and there is no evidence of puzzles. We document evidence compatible with many of the standard channels of monetary transmission and reflected in a deterioration of prices, domestic demand, labor market conditions, investments, and household wealth (e.g., Mishkin 1996). We analyze in detail the response of interest rates at short, medium, and very long maturities and find important but very short-lived effects of policy on the yield curve (Romer and Romer 2000, Ellingsen and Soderstrom 2001). Also, we find evidence of a powerful credit channel that magnifies the size of the economic contraction

[4] Market-based monetary surprises are the high-frequency price revisions in traded interest rates futures that are triggered by a policy announcement. In using financial markets instruments to measure the unexpected component of monetary policy, we connect to a large literature pioneered by Rudebusch (1998); Kuttner (2001); and Gürkaynak, Sack, and Swanson (2005) and whose notable contributions include, among others, Bernanke and Kuttner (2005); Gürkaynak (2005); Hamilton, Pruitt, and Borger (2011); Gilchrist, López-Salido, and Zakrajšek (2015); Campbell et al. (2016); Caldara and Herbst (2019). Thapar (2008) and Barakchian and Crowe (2013) have proposed identifications based on monetary surprises that control for the central bank's internal forecasts. Differently from these papers, our methodology incorporates intuition stemming from models of imperfect information.

through the responses of both credit and financial markets (Bernanke and Gertler 1995, Gertler and Karadi 2015, Caldara and Herbst 2019). Moreover, we document a deterioration of the external position sustained by a significant appreciation of the domestic currency. The expectational channel is also activated: following a contractionary monetary policy shock, agents revise their macroeconomic forecasts in line with the deteriorating fundamentals.

Finally, in Section VI, we assess the model and sample dependence of our results and their sensitivity to model misspecification. Indeed, this is an important concern in the literature. As thoroughly discussed in Ramey (2016), other than on the chosen identification strategy, the sign of the responses of crucial variables such as output and prices depends on the sample and empirical specification adopted and on whether the dynamic responses are obtained from standard VAR models or from Local Projections (LP) methods. We compare results from three empirical specifications: a vector autoregression, a standard local projection method (LP) (Jordà 2005), and a Bayesian version of Local Projections (BLP) (Miranda-Agrippino and Ricco 2021a) that optimally balances between bias and estimation variance. The rationale for this test is as follows. Low-order VARs with small set of controls that are often used in the empirical literature are likely to be misspecified; in this case, the bias in the estimated coefficients is compounded over the horizons. On the other hand, Local Projection impulse response functions (IRFs) have the desirable property of being potentially robust to misspecification. This flexibility, however, comes with the added cost of quickly drying up degrees of freedom, with consequential high estimation uncertainty particularly in small samples. A Bayesian approach to Local Projection (BLP) retains the flexibility of LP and hence the robustness to model (mis)specification while at the same time efficiently dealing with estimation uncertainty.[5] We document that in small models and for short samples, residual puzzles may still arise because of the limited ability of standard methods to cope with either misspecification (VAR) or estimation uncertainty (LP), even after having corrected the monetary policy instrument for the information transfer. However, Bayesian Local Projection delivers results that are stable over time and seldom display puzzles.[6] We look at this as a further indication of the robustness of our findings even for severely misspecified models.

This paper fits in the recent literature that explores the implications of the information effects of monetary policy announcements. Two closely related papers are Jarociński and Karadi (2020) and Cieslak and Schrimpf (2019). These use a combination of high-frequency responses of asset prices and sign restrictions to separate monetary policy shocks from other news shocks, and produce complementary evidence of contamination of high-frequency surprises by information on other macroeconomic shocks. With similar techniques, Andrade and Ferroni (2016) extract

[5] BLP responses are estimated using conjugate priors either extending the Minnesota prior approach or, alternatively, centered around an iterated VAR estimated on a presample. Intuitively, the prior gives weight to the belief that economic time series processes can be described in first approximation by linear models such as VARs. Extending the argument in Giannone, Lenza, and Primiceri (2015), we treat the overall informativeness of the priors as an additional model parameter for which we specify a prior distribution, and choose it as the maximizer of the posterior likelihood. As a result, the posterior mean of BLP IRFs is an optimally weighted combination of VAR and LP-based IRFs.

[6] While not ruling out the possibility of time variation in the transmission coefficients of monetary policy (see Primiceri 2005), our results show that the effects of monetary policy are more stable than previously reported.

the information content of forward guidance announcements in the Euro Area. Differently from these works, our approach does not require the use of sign restrictions and provides a readily employable instrument for monetary policy shocks. Moreover, while these works focus on the content of monetary policy announcements as perceived by market participants, in our approach, we explicitly model and control for the information transfer. In doing so, we expand on the approach of Campbell et al. (2012) that proposed to use (agents) expectations as represented by survey data to capture the information effects in (or Delphic component of) forward guidance announcements.

I. A Simple Model of Noisy Information

Two implications of models of imperfect information are important for the identification of monetary policy shocks. First, as observed in Coibion and Gorodnichenko (2015), a common prediction of models of imperfect information is that average expectations respond more gradually to shocks to fundamentals than do the variables being forecasted. This implies that revisions of expectations—and importantly, movements in market prices—can be correlated over time and contain information on both current and past structural shocks. Second, due to the asymmetry of information between policymakers and market participants, observable policy actions can convey information about fundamentals (see Melosi 2017, Romer and Romer 2000). In this section, we introduce a simple model of noisy and asymmetric information that can account for these features and provide intuition for our approach.[7]

Let us consider an economy whose k-dimensional vector of macroeconomic fundamentals evolves following an autoregressive process

$$x_t = \rho x_{t-1} + \xi_t, \qquad \xi_t \sim \mathcal{N}\left(0, \Sigma_\xi\right), \tag{1}$$

where ξ_t is the vector of structural shocks. Any period t is divided into two stages: an opening stage $\underline{t}$ and a closing stage $\overline{t}$. At $\underline{t}$, shocks are realized. Agents and central banks do not observe x_t directly; rather, they use a Kalman filter to form expectations about x_t based on the private noisy signals that they receive. We use $s_{i,\underline{t}}$ and $s_{cb,\underline{t}}$ to denote the signals received at time $\underline{t}$ by private agents and the central bank, respectively. Similarly, we use $F_{i,\underline{t}}$ and $F_{cb,\underline{t}}$ to denote their respective conditional forecasts. The information flow is sketched in Figure 1.

Agents can trade securities (e.g., futures contracts) based on i_{t+h}, the realization of the policy rate at time $t+h$. The price of a futures contract on i_{t+h} reflects their aggregate expectation about x_t, as follows:

$$p_{\underline{t}}\left(i_{t+h}\right) = F_{\underline{t}} x_{t+h} + \mu_t, \tag{2}$$

[7] Derivations of the main formulas are in the online Appendix.

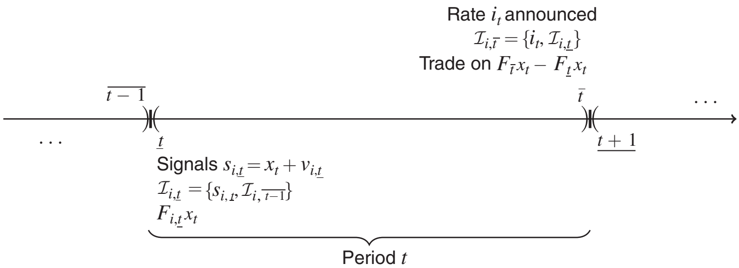

FIGURE 1. THE INFORMATION FLOW

Notes: Each period t has a beginning $\underline{t}$ and an end $\bar{t}$. At $\underline{t}$, agents (both private and central bank) receive noisy signals $s_{i,\underline{t}}$ about the economy x_t and update their forecasts $F_{i,\underline{t}}x_t$ based on their information set $\mathcal{I}_{i,\underline{t}}$. At $\bar{t}$, the central bank announces the policy rate i_t based on its forecast $F_{cb,\underline{t}}x_t$. Agents observe i_t, infer $F_{cb,\underline{t}}x_t$, and form $F_{i,\bar{t}}x_t$. Trade is a function of the aggregate expectation revision between $\underline{t}$ and $\bar{t}$.

where μ_t is a stochastic component, such as the risk premium in Gürkaynak, Sack, and Swanson (2005), or a stochastic process related to the supply of assets (see Hellwig 1980, Admati 1985).

At $\bar{t}$, and conditional on its own forecast $F_{cb,\underline{t}}x_t$, the central bank sets the interest rate for the current period using a Taylor rule:

$$i_t = \phi_0 + \phi_x' F_{cb,\underline{t}} x_t + u_t + w_{t|t-1}, \tag{3}$$

where u_t denotes the monetary policy shock.[8] Also, the central bank can announce—or leak—at time $t-1$ a deviation from the Taylor rule, $w_{t|t-1}$, that takes places at time t.[9] Having observed the current policy rate, agents update their forecasts and trade at $\bar{t}$. Conditional on i_{t-1}, observing the interest rate is equivalent to receiving a public signal with common noise $\tilde{s}_{cb,\bar{t}}$ from the central bank. Because of this forecast update triggered by the policy announcement, the price of futures contracts is revised by an amount proportional to the average (in population) revision of expectations, that is

$$p_{\bar{t}}(i_{t+1}) - p_{\underline{t}}(i_{t+1}) \propto (F_{\bar{t}}x_{t+1} - F_{\underline{t}}x_{t+1}), \tag{5}$$

[8] Interestingly, the interest rate smoothing in the monetary policy rule arises naturally from the signal extraction problem faced by the central bank. Indeed, it is possible to rewrite equation (3) as

$$i_t = \left[(1-K_{cb})\rho\right]\phi_0 + (1-K_{cb})\rho i_{t-1} + K_{cb}\phi_x' s_{cb,\underline{t}} - (1-K_{cb})\rho u_{t-1} + u_t, \tag{4}$$

where K_{cb} is the central bank's Kalman gain. The policy rate at any time t is a function of current and past signals and of current and past monetary policy shocks.

[9] This announced deviation—that can be thought of as due to either implicit or explicit forward guidance—creates a wedge between Taylor rule residuals and monetary policy shocks. Additionally, Taylor rule deviations can also be autocorrelated and hence forecastable. In these cases, the monetary policy shocks would be different from the residuals of a regression of the policy rate on central bank's private forecasts. For the sake of simplicity, we abstract from such case in the model, while testing empirically for predictability and autocorrelation of residuals form an empirically estimated Taylor rule.

where $F_{\underline{t}} x_{t+1}$ and $F_{\bar{t}} x_{t+1}$ are the average forecast updates that follow $s_{i,\underline{t}}$ and $\tilde{s}_{cb,\bar{t}}$.

LEMMA: *Following a central bank policy announcement, aggregate expectations revisions evolve as*

$$
\begin{aligned}
(6)\qquad F_{\bar{t}} x_t - F_{\underline{t}} x_t = {} & (1 - K_2)(1 - K_1)\left[F_{\overline{t-1}} x_t - F_{\underline{t-1}} x_t\right] \\
& + K_2(1 - K_1)\,\xi_t + K_2\left[\nu_{cb,\underline{t}} - (1 - K_1)\rho\,\nu_{cb,\underline{t-1}}\right] \\
& + K_2\left(K_{cb}\phi_x'\right)^{-1}\Big[u_t - \rho(2 - K_{cb} - K_1)\,u_{t-1} \\
& \qquad + (1 - K_1)(1 - K_{cb})\,\rho^2 u_{t-2}\Big],
\end{aligned}
$$

where K_1 and K_2 denote the agents' Kalman gains employed in $F_{i,\underline{t}}$ and $F_{i,\bar{t}}$, respectively; K_{cb} is the central bank's Kalman gain; u_t is a monetary policy shock; and ν_{cb} is the central bank's observational noise.

Proofs are collected in the online Appendix. Two emerging features of models of imperfect information that have important implications for the identification of monetary policy shocks are in evidence in equation (6). First, average expectation revisions (and thus high-frequency surprises)—a direct measure of the shocks under full information—are orthogonal neither to their past nor to past available information due to the slow absorption of new information over time. Second, observable policy actions can transfer information about economic fundamentals from the policymaker to market participants. Indeed, as is visible in equation (6), agents update their expectations by extracting from the policy announcement information about the structural shocks ξ_t. This is the "Fed information effect" of Romer and Romer (2000) and Nakamura and Steinsson (2018), or the "signalling channel" as in Melosi (2017) and also Tang (2013) and Hubert and Maule (2016). The implicit disclosure of information can strongly influence the transmission of monetary impulses and the central bank's ability to stabilize the economy. Empirically, if not accounted for, it can lead to both price and output puzzles. In fact, a policy rate hike can be interpreted by informationally constrained agents either as a deviation of the central bank from its monetary policy rule—i.e., a contractionary monetary shock—or as an endogenous response to inflationary pressures expected to hit the economy in the near future. Despite both resulting in a policy rate increase, these two scenarios imply profoundly different evolutions for macroeconomic aggregates and agents' expectations.[10]

Importantly, equation (6) provides us with testable predictions about market-based monetary surprises: in the presence of imperfect information, they are (i) serially correlated, (ii) predictable using other macroeconomic variables, and (iii) correlated with the central bank's projections of relevant macroeconomic variables.

[10]It is also worth noticing that the third term in equation (6) is the aggregate noise contained in the policy announcement, due to the central bank's noisy observation of the state of the economy. This too can be thought of as another exogenous policy shift (see Orphanides 2003).

II. Testing for Imperfect Information

In this section, we empirically document the three testable implications discussed in the previous section. In particular, Tables 1, 2, and 3 report, respectively, the tests for (i) correlation with the Fed's internal forecasts, (ii) serial correlation, and (iii) predictability with lagged state variables, for the leading instruments for monetary policy shocks.

Table 1 presents the estimated coefficients and relative significance level of the projection of high-frequency market surprises in the fourth federal funds futures (FF4) over Greenbook forecasts and revisions to forecasts for output, inflation, and unemployment. Specifically, we use the intraday movements in the fourth federal funds futures contracts that are registered within a 30-minute window surrounding the time of the FOMC announcements, as proposed by Gürkaynak, Sack, and Swanson (2005). These contracts have an average maturity of about three months and settle based on the average effective federal funds rate prevailing on the expiry month. Their price can therefore be thought of as embedding markets' forecasts about future policy rates. The regression is run at daily frequency on all surprises registered between 1990 and 2009.

The first column corresponds to a regression similar to that in Romer and Romer (2004) and includes forecasts for output and inflation relative to the previous quarter and up to three quarters ahead; nowcasts for the unemployment rate; and forecast revisions for output, inflation, and unemployment relative to the previous quarter and up to two quarters ahead. We will use this specification for the construction of our instrument in the next section. The null of joint nonsignificance of the coefficients is rejected at the 5 percent level. Results show that high-frequency surprises correlate with the central bank's private forecasts, in line with the intuition in our model.[11] However, the interpretation of the individual coefficients is limited by the multicollinearity of forecasts for the same variable at different horizons. In columns 2 to 5, we evaluate the predictive content of forecasts and forecast revisions grouped by horizon. The null of joint nonsignificance is rejected for all horizons up to one quarter ahead. Results suggest that the information transfer is mostly related to the central bank assessment of the short-term macroeconomic outlook. Moreover, output forecasts have significant and positive coefficients. This is consistent with these regressors capturing aggregate demand shocks and their effect on prices via the Phillips curve. The negative coefficients on inflation forecasts may capture the residual effects of supply shocks to which the central bank may be less responsive.

A potentially important concern relates to the role of unscheduled meetings, where the FOMC takes urgent decisions in moments of particular economic distress, as it happened, for example, during the Great Recession. These unexpected meetings, which coalesce markets attention, may in fact be the ones responsible for the information channel. We address this concern by repeating the regression in Table 1

[11] Related results are in Barakchian and Crowe (2013), Gertler and Karadi (2015), Ramey (2016).

Table 1—Central Bank Information Channel

	(1)	(3)	(4)	(5)	(6)
Output forecasts					
$h = -1$	0.001	0.005			
	(0.004)	(0.002)			
$h = 0$	0.006		0.009		
	(0.006)		(0.003)		
$h = 1$	0.001			0.003	
	(0.009)			(0.004)	
$h = 2$	−0.001				0.001
	(0.008)				(0.005)
$h = 3$	−0.004				
	(0.008)				
Inflation forecasts					
$h = -1$	−0.009	−0.008			
	(0.006)	(0.004)			
$h = 0$	0.012		−0.000		
	(0.008)		(0.005)		
$h = 1$	−0.036			−0.014	
	(0.016)			(0.006)	
$h = 2$	0.040				−0.008
	(0.020)				(0.006)
$h = 3$	−0.018				
	(0.019)				
Unemployment forecasts					
$h = -1$		0.002			
		(0.005)			
$h = 0$	0.003		0.001		
	(0.005)		(0.004)		
$h = 1$				−0.000	
				(0.003)	
$h = 2$					−0.003
					(0.003)
$h = 3$					
Output forecasts revisions					
$h = -1$	−0.007	−0.010			
	(0.006)	(0.005)			
$h = 0$	0.000		0.005		
	(0.008)		(0.005)		
$h = 1$	0.008			0.006	
	(0.011)			(0.007)	
$h = 2$	0.010				−0.005
	(0.010)				(0.010)
Inflation forecasts revisions					
$h = -1$	−0.004	−0.002			
	(0.010)	(0.009)			
$h = 0$	−0.002		0.004		
	(0.010)		(0.009)		
$h = 1$	0.043			0.018	
	(0.021)			(0.012)	
$h = 2$	−0.021				0.023
	(0.025)				(0.018)

(continued)

Table 1—Central Bank Information Channel (*continued*)

Unemployment forecasts revisions					
$h = -1$	0.068	0.053			
	(0.067)	(0.065)			
$h = 0$	−0.015		0.009		
	(0.047)		(0.028)		
$h = 1$	−0.098			−0.028	
	(0.076)			(0.028)	
$h = 2$	0.104				−0.023
	(0.064)				(0.029)
Constant	−0.011	−0.022	−0.040	0.005	0.016
	(0.045)	(0.036)	(0.037)	(0.034)	(0.036)
R^2	0.044	0.027	0.045	0.040	−0.004
F-statistic	1.651	2.024	2.636	2.436	1.045
p-value	0.039	0.065	0.018	0.027	0.398
Observations	186	186	186	186	186

Notes: Projection of high-frequency market-based surprises on Greenbook forecasts. Robust standard errors are in parentheses. Dependent variable is the 30-minute adjustment in the price of the fourth federal funds future (FF4) around all FOMC announcements in the sample 1990:2009. Details on the specifications are reported in the text.

using market surprises registered around scheduled FOMC meetings only and found that results are robust (online Appendix).[12]

In Table 2, we report tests of autocorrelation in both high-frequency and narrative instruments for monetary policy shocks. High-frequency surprises are aggregated at monthly frequency using different schemes. The first column reports results for an instrument defined as the sum within the month of all the FF4 surprises registered between 1990 and 2009. In the second column, only scheduled FOMC meetings are included. The third column reports results for the instrument of Gertler and Karadi (2015). Their monthly aggregation accounts for the date of the FOMC meeting within the month and weights the surprises by assuming a month duration for each event.[13] In the last column of Table 2, we report results relative to the narrative instrument of Romer and Romer (2004).[14] The construction of the narrative instrument (MPN_t) amounts to running a regression of the change in policy rate on central bank's forecasts, motivated by an empirical Taylor rule. The residuals are then used as a measure of the shocks u_t.

Results in Table 2 show that serial correlation is present in the series of high-frequency surprises that are registered around scheduled FOMC meetings only

[12] Results are robust to running the regressions over the samples 1994:2009 and 1990:2014. In 1994, the FOMC changed the way in which policy decisions were communicated. 2009 is chosen as the onset of the zero lower bound (ZLB). 2014 corresponds to our latest available observation. All robustness checks are reported in the online Appendix.

[13] In particular, for each day of the month, they cumulate the surprises on any FOMC days during the last 31 days (e.g., on February 15, we cumulate all the FOMC day surprises since January 15), and, second, they average these monthly surprises across each day of the month. Equivalently, this can be achieved by first creating a cumulative daily surprise series by cumulating all FOMC day surprises, then, second, by taking monthly averages of these series, and, third, obtaining monthly average surprises as the first difference of this series.

[14] We use an extension of this series up to the end of 2007 constructed following the same methodology of Romer and Romer (2004).

Table 2—Serial Correlation in Instruments for Monetary Policy

	$FF4_t$	$FF4_t^{\dagger}$	$FF4_t^{GK}$	MPN_t
instrument_{t-1}	0.065	−0.164	0.380	0.014
	(0.090)	(0.057)	(0.137)	(0.091)
instrument_{t-2}	−0.025	−0.048	−0.164	0.227
	(0.119)	(0.066)	(0.073)	(0.087)
instrument_{t-3}	0.145	−0.066	0.308	0.381
	(0.130)	(0.073)	(0.150)	(0.102)
instrument_{t-4}	0.179	−0.007	−0.035	0.075
	(0.105)	(0.068)	(0.094)	(0.102)
Constant	−0.016	−0.011	−0.011	0.011
	(0.005)	(0.004)	(0.003)	(0.015)
R^2	0.026	0.001	0.168	0.172
F-statistic	1.459	2.279	2.965	7.590
p-value	0.217	0.063	0.021	0.000
Observations	167	167	166	152

Notes: AR(4) for instruments in each column. From left to right, the monthly surprise in the fourth federal funds future ($FF4_t$), the monthly surprise in the fourth federal funds future in scheduled meetings only ($FF4_t^{\dagger}$), the instrument in Gertler and Karadi (2015) ($FF4_t^{GK}$), and the narrative series of Romer and Romer (2004) (MPN_t). 1990:2009. Robust standard errors are in parentheses.

($FF4_t^{\dagger}$), in line with the intuition of our simple model of Section I. A limiting factor in our analysis is the fact that there are only eight meetings scheduled in each given year, which creates missing values in the regression.[15] The autocorrelation structure is weaker for the series that also includes the unscheduled FOMC meetings ($FF4_t$). This is likely to be due to the unsystematic nature of these events. On the other hand, the high-frequency instrument of Gertler and Karadi (2015) is strongly autocorrelated. This is partially due to the weighting scheme used for the monthly aggregation discussed above, as also observed in, e.g., Stock and Watson (2012) and Ramey (2016). On balance, while not fully conclusive, this evidence is compatible with the presence of information frictions in the economy. Finally, the null is strongly rejected for the narrative series of Romer and Romer (2004) (MPN_t) (Stock and Watson 2012).

In Table 3, we propose a test of predictability using past information. In particular, we project the different measures of monetary policy shocks on a set of lagged macro-financial factors extracted from the collection of monthly variables assembled in McCracken and Ng (2015). The dataset that we use for the factors extraction counts over 130 monthly series that cover all the main macroeconomic aggregates, and a number of financial indicators. The factors enter the regressions with a month's lag. Results in Table 3 confirm the predictability of market-based monetary surprises using past information. They also show that narrative accounts of "unanticipated" interest rate changes are similarly predictable by state variables, which are a function of past structural shocks. This last result is consistent with the

[15] As pointed out in Coibion and Gorodnichenko (2012), the OLS coefficients in the autoregression can be biased as a consequence of the presence of noisy signals. The bias in our case is likely to be negative (see online Appendix, equation A.18).

Table 3—Predictability of Monetary Policy Instruments

	$FF4_t$	$FF4_t^{\dagger}$	$FF4_t^{GK}$	MPN_t
$f_{1,t-1}$	−0.012	−0.007	−0.011	−0.087
	(0.006)	(0.003)	(0.004)	(0.021)
$f_{2,t-1}$	0.001	0.000	0.004	−0.009
	(0.003)	(0.002)	(0.002)	(0.010)
$f_{3,t-1}$	0.002	0.003	−0.001	0.000
	(0.005)	(0.004)	(0.004)	(0.012)
$f_{4,t-1}$	0.015	0.008	0.008	0.060
	(0.007)	(0.004)	(0.004)	(0.023)
$f_{5,t-1}$	0.002	−0.005	−0.000	0.002
	(0.007)	(0.004)	(0.004)	(0.026)
$f_{6,t-1}$	−0.011	−0.009	−0.006	−0.003
	(0.005)	(0.003)	(0.003)	(0.011)
$f_{7,t-1}$	−0.010	−0.009	−0.005	−0.041
	(0.006)	(0.004)	(0.004)	(0.016)
$f_{8,t-1}$	−0.001	−0.002	0.000	−0.028
	(0.003)	(0.002)	(0.003)	(0.012)
$f_{9,t-1}$	−0.002	−0.001	−0.004	−0.036
	(0.004)	(0.003)	(0.003)	(0.021)
$f_{10,t-1}$	−0.004	−0.001	0.000	0.030
	(0.005)	(0.003)	(0.003)	(0.012)
Constant	−0.014	−0.006	−0.011	0.010
	(0.004)	(0.003)	(0.003)	(0.011)
R^2	0.075	0.097	0.145	0.182
F-statistic	2.297	2.363	3.511	3.446
p-value	0.011	0.009	0.000	0.000
Observations	239	239	268	216

Notes: Regressions include a constant and one lag of the dependent variable. 1990:2009. From left to right, the monthly surprise in the fourth federal funds future ($FF4_t$), the monthly surprise in the fourth federal funds future in scheduled meetings only ($FF4_t^{\dagger}$), the instrument in Gertler and Karadi (2015) ($FF4_t^{GK}$), and the narrative series of Romer and Romer (2004) (MPN_t). The ten dynamic factors are extracted from the set of monthly variables in McCracken and Ng (2015). Robust standard errors are in parentheses.

autocorrelation reported in Table 2. We also observe that it may be an indication of the fact that narrative instruments may also be contaminated by announced policy shifts as is the case, e.g., for forward guidance.[16] It is important to observe that factors are estimated using last vintage data, which are likely to incorporate revisions to early releases. While this may not be information readily available to agents, it is worth to observe that this is an indication of imperfect information. In fact, in a perfect information world, markets aggregate information efficiently, and there is no role for either data revisions or national accounting offices. Taking stock of this evidence, in the next section, we propose a novel instrument that accounts for the presence of information frictions in the economy.

[16] See, e.g., equation (3). Also, if the central bank sets the policy rate conditioning on other indicators such as financial and fiscal variables (see, e.g., Croushore and van Norden 2018), the projection residuals will also be endogenous to these variables. This again may show up as predictability with factors.

III. An Informationally Robust Instrument

Accounting for the presence of information frictions, we define monetary policy shocks as shifts to the policy rate that are both unforeseen by market participants and are not due to the central bank's concerns about either current or anticipated changes in economic conditions. Hence, building on the high-frequency identification of Gertler and Karadi (2015) and on Romer and Romer's (2004) narrative approach, we propose a novel instrument for monetary policy shocks that takes into account both the slow absorption of information in the economy and the signaling channel of monetary policy that arises from the asymmetry of information sets between the central bank and market participants.

Specifically, we construct our instrument for monetary policy shocks as the component of high-frequency market surprises triggered by policy announcements that is orthogonal to both the central bank's economic projections and to past market surprises. We proceed in three steps. First, we project high-frequency market-based surprises in the fourth federal funds futures around FOMC announcements on Greenbook forecasts and forecast revisions for real output growth, inflation (measured as the GDP deflator), and the unemployment rate, as in Romer and Romer (2004), to control for the central bank's private information and hence for the central bank information channel.[17] We run the following regression at FOMC meeting frequency:

$$(7) \qquad FF4_m = \alpha_0 + \sum_{j=-1}^{3} \theta_j F_m^{cb} x_{q+j} + \sum_{j=-1}^{2} \vartheta_j \left[F_m^{cb} x_{q+j} - F_{m-1}^{cb} x_{q+j}\right] + MPI_m.$$

Here, $FF4_m$ denotes the high-frequency market-based monetary surprise computed around the FOMC announcement indexed by m, $F_m^{cb} x_{q+j}$ denotes Greenbook forecasts for the vector of variables x at horizon $q + j$ that are assembled prior to each meeting, and $[F_m^{cb} x_{q+j} - F_{m-1}^{cb} x_{q+j}]$ denotes revisions to forecasts between consecutive FOMC meetings. The forecast horizon is expressed in quarters, and q denotes the current quarter. These forecasts are typically published a week prior to each scheduled FOMC meeting and can be thought of as a proxy of the information set of the FOMC at the time of making the policy decision. For each surprise, the latest available forecast is used.[18] This first step delivers as a residual an instrument for monetary policy shocks (MPI_m) at meeting frequency that controls for the transfer of information that implicitly happens at the time of FOMC announcements.

Second, we construct a monthly instrument by summing the daily MPI_m within each month. In the vast majority of cases, we only have one surprise per month; in these cases, the monthly surprise simply equals the daily one. Similarly, months without FOMC meetings are assigned a zero. Equivalent aggregation methods are adopted in, e.g., Stock and Watson (2012) and Caldara and Herbst (2019).

[17] Following Romer and Romer (2004), we only include the nowcast for the level of the unemployment rate to mitigate the effects of the high correlation between output and unemployment.

[18] For intermeeting decisions, we use the last available forecast. In doing so, we run the risk of not fully controlling for all the transfer of information. In robustness tests, we also run equation (7) on scheduled FOMC meetings only and find that results are largely unchanged. Results are reported in the online Appendix.

Finally, we account for the slow absorption of information by the agents that is a trademark of models of imperfect information (see Coibion and Gorodnichenko 2015) by removing the autoregressive component in the monthly surprises. Let $\overline{MPI}_t$ denote the result of the monthly aggregation described in the previous step. Our monthly monetary policy instrument MPI_t is constructed as the residuals of the following regression:

$$\overline{MPI}_t = \phi_0 + \sum_{j=1}^{12} \phi_j \overline{MPI}_{t-j} + MPI_t. \tag{8}$$

We run the regression specified in equation (8) using only observations that correspond to nonzero $\overline{MPI}_t$ readings for the dependent variable. In months without meetings, MPI_t is equal to zero.

The stylized model of Section I provides the intuition for the construction of our instrument in equations (7)–(8). The Greenbook forecasts (and revisions) directly control for the information set of the central bank and hence for the macroeconomic information transferred to the agents through the announcement. Even in the presence of misspecification in the empirical Taylor rule adopted in equation (7), central bank's forecasts for output, inflation, and unemployment are likely to span the space of the macro shocks to which the monetary authority responds in setting the policy stance. This, together with the lagged surprises, tackles the dependence of high-frequency instruments on other contemporaneous and past macroeconomic shocks.[19] In Figure 2, we plot the market monetary surprise aggregated at monthly frequency by summing daily surprises ($FF4_t$, orange line) and the instrument constructed with our approach (MPI_t, blue line). It is worth noting that discrepancies between the two series are particularly evident during times of economic distress.

IV. The Impact of Different Identifying Assumptions

In this section, we explore the implications of the different information content of alternative instruments for the identification of monetary policy shocks. The section is organized as follows. First, we compare the dynamic responses identified using our instrument with two alternatives: the narrative series of Romer and Romer (2004) and the high-frequency series of Gertler and Karadi (2015). Second, we compare impact responses across instruments and model specifications. These can reveal contamination of the instruments by past shocks. Third, we evaluate responses to the endogenous component of monetary surprises and show that they are compatible with the presence of an information channel of monetary policy.

Dynamic Responses under Alternative Identifications.—Figure 3 reports impulse response functions to a monetary policy shock estimated in a VAR that encompasses those used in Coibion (2012) and Gertler and Karadi (2015). The vector of endogenous variables includes an index of industrial production, the unemployment

[19] We report robustness of the effects of monetary policy shocks on the specification of equation (7) in the online Appendix. Results are robust to changing the set of regressors, so long as short horizon forecasts (and revisions) are included.

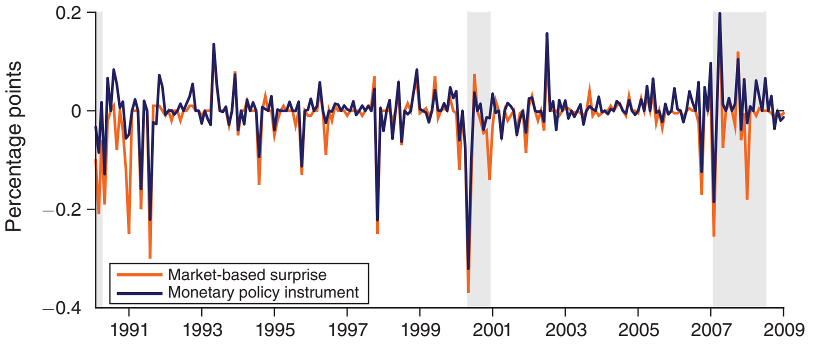

Figure 2. Informationally Robust Instrument for Monetary Policy Shocks

Notes: Market-based surprises conditional on private agents' information set $FF4_t$ (orange line), residual to equation (8) MPI_t (blue line). Shaded areas denote NBER recessions.

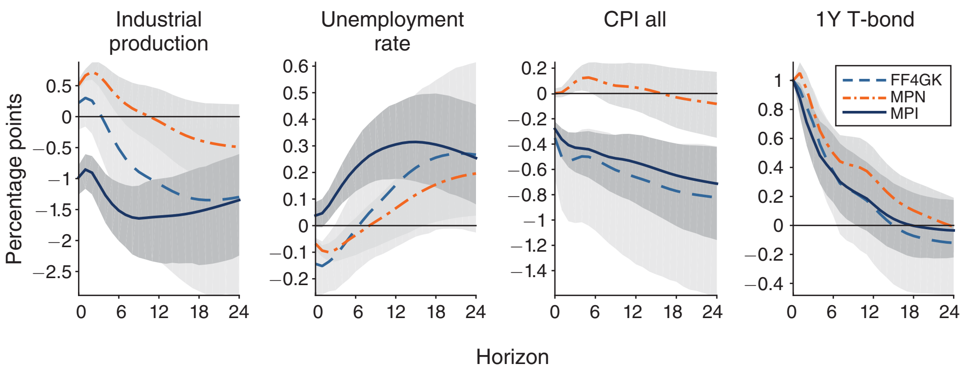

Figure 3. Responses to Monetary Policy Shock under Different Identifications

Notes: Six-variable VAR. Shock identified with Gertler and Karadi's (2015) average monthly market surprise (teal, dashed), extended narrative measure of Romer and Romer (2004) (orange, dash-dotted), and informationally robust MPI_t series (dark blue lines). The shock is normalized to induce a 100 basis point increase in the 1-year rate. Sample 1979:1–2014:12. Shaded areas are 90 percent posterior coverage bands.

rate, the consumer price index, a commodity price index, the excess bond premium (EBP) of Gilchrist and Zakrajšek (2012), and the policy rate.[20] By keeping the VAR composition fixed, we can interpret the differences in the IRFs as an indication of the different information content of the instruments used for the identification. The dashed teal lines report the responses to a monetary policy shock identified using the high-frequency instrument of Gertler and Karadi (2015)—$FF4_t^{GK}$. The orange (dash-dotted) lines are responses identified using the narrative instrument of Romer

[20] Because our sample includes the zero lower bound, we choose the 1-year nominal rate as our policy variable as in Gertler and Karadi (2015) and normalize the responses such that the shock increases the policy rate by 1 percent on impact. All variables are monthly. Impulse response functions are from a VAR(12) estimated in (log) levels from 1979:1 to 2014:12. The VAR is estimated with Bayesian techniques and standard macroeconomic priors. The tightness of the prior is set as in Giannone, Lenza, and Primiceri (2015). Results on robustness to the sample are in Section VI. Details on the data used are in the online Appendix.

Table 4—First-Stage Statistics: VAR of Figure 3

	$FF4_t$		MPI_t		$FF4_t^{GK}$		MPN_t	
F-statistic	23.688	[12.23 29.09]	15.308	[9.61 16.75]	13.154	[5.07 19.70]	67.195	[53.59 75.75]
Reliability	0.557	[0.41 0.57]	0.263	[0.20 0.28]	0.308	[0.21 0.34]	0.469	[0.42 0.50]

Notes: Top row: F-statistics of the first-stage regression of the reduced-form innovations on the instrument. Bottom row: reliability of the instrument. Ninety percent confidence intervals in square brackets. VAR composition: industrial production, unemployment rate, consumer price index, commodity price index, excess bond premium, one-year rate.

and Romer (2004)—MPN_t. Lastly, the solid blue lines indicate the effects of a monetary disturbance identified using our informationally robust instrument MPI_t. In each case, we use the common sample between the VAR innovations and the external instrument to estimate the impact responses.[21] Table 4 reports first-stage F-statistics and reliability of the three instruments for the VAR of Figure 3. We also include the original $FF4_t$ in the table for comparison. All the instruments pass conventional tests for instruments' relevance. We note, however, that these tests remain silent on the exogeneity of each; in fact, contamination by other macroeconomic shocks could inflate the first-stage F-statistics. The three identifications produce notably different responses in two respects: (i) the use of the narrative instrument triggers an initial price puzzle and a subsequent nonsignificant response of prices, and (ii) both the narrative and the high-frequency instruments elicit positive impact responses of output and negative impact responses of unemployment and hence produce initial real activity puzzles. Conversely, the informationally robust instrument gives rise to neither price nor output puzzles. Interestingly, industrial production drops on impact and significantly contracts over the horizon of the IRF. Importantly, the responses to a monetary policy shock obtained with this identification are consistent with standard macroeconomic theory: a contractionary monetary policy shock induces a contraction in output, a rise in unemployment, and a reduction in prices.

We compare these responses with those in Figure 4, where identification is conducted using the same three instruments but the IRFs are estimated in a VAR with a slightly different specification of the information set. Specifically, we remove the excess bond premium variable. The resulting VAR composition is a fairly standard one in empirical macro and matches those used in, e.g., both Coibion (2012) and Ramey (2016) (first-stage statistics for this VAR are reported in Table 5). In this new set of responses, the IRFs obtained from the narrative and the $FF4_t^{GK}$ instrument show a marked instability when compared with the ones reported in Figure 3. Quite crucially, the puzzles become more pronounced and long-lasting (see also Ramey 2016). Conversely, responses estimated with our instrument remain stable across the two specifications.

Three remarks summarize the comparison. First, both the narrative and the average market surprises produce responses that lack robustness to small changes to the information set, while the new instrument does not. Second, the narrative and the

[21] Identification with external instruments entails regressing reduced-form innovations onto the instrument. Because our instrument is a residual generated regressor, OLS-based inference is asymptotically correct (Pagan 1984).

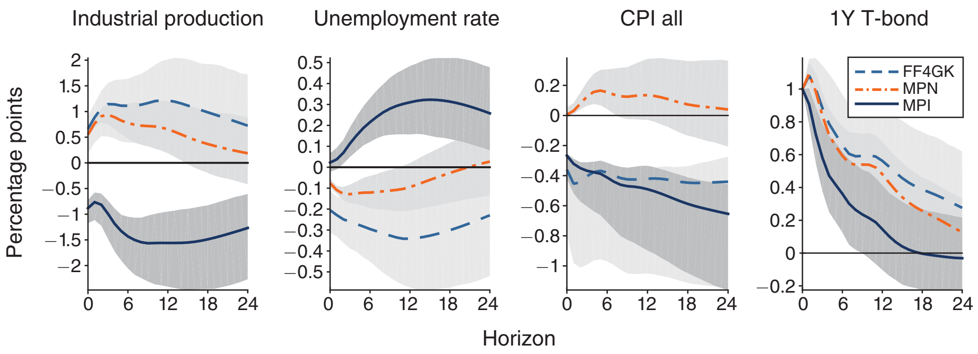

Figure 4. Responses to Monetary Policy Shock under Different Identifications

Notes: Five-variable baseline VAR. Shock identified with Gertler and Karadi's (2015) average monthly market surprise (teal, dashed), extended narrative measure of Romer and Romer (2004) (orange, dash-dotted), and informationally robust MPI_t series (dark blue lines). The shock is normalized to induce a 100 basis point increase in the 1-year rate. Sample 1979:1–2014:12. Shaded areas are 90 percent posterior coverage bands.

Table 5—First-Stage Statistics: VAR of Figure 4

	$FF4_t$		MPI_t		$FF4_t^{GK}$		MPN_t	
F-statistic	24.172	[13.24 30.14]	15.027	[9.47 16.71]	13.277	[5.43 19.26]	67.608	[54.52 74.85]
Reliability	0.522	[0.38 0.55]	0.233	[0.19 0.25]	0.264	[0.19 0.27]	0.445	[0.40 0.47]

Notes: Top row: F-statistics of the first-stage regression of the reduced-form innovations on the instrument. Bottom row: reliability of the instrument. Ninety percent confidence intervals in square brackets. VAR composition: industrial production, unemployment rate, consumer price index, commodity price index, excess bond premium, one-year rate.

average market surprises elicit either short- or long-lived output and price puzzles in both specifications, while the new instrument does not. Third, the impact responses of the narrative instrument and the average market surprises are not always coherent with economic theory and show signs of instability (notably for IP).

Impact Effects of Monetary Policy Shocks.—To rationalize the results above, it is worth recalling the assumptions under which it is possible to identify structural shocks in a VAR by using external instruments (see Stock and Watson 2018, Mertens and Ravn 2013). For a correctly specified VAR able to capture the data generating process, and assuming invertibility in the structural shocks,[22] given an instrument z_t, it is possible to identify a shock of interest—e.g., a monetary policy shock u_t^{mp}—if

$$\text{(9)} \qquad \text{(i)} \qquad E\left[u_t^{mp} z_t'\right] = \phi,$$

$$\text{(10)} \qquad \text{(ii)} \qquad E\left[u_t^{mp} z_t'\right] = 0,$$

[22] The structural shocks u_t are invertible if $u_t = A_0 \varepsilon_t$, where A_0 identifies the mapping between the structural shocks and the reduced-form one-step-ahead forecast errors ε_t.

where u_t^{mp} and $u_t^{\cancel{mp}}$ denote, respectively, the monetary policy shock and any other shock in the system. These are the standard requirements of relevance of the instrumental variable and exogeneity with respect to other contemporaneous shocks.[23] If also a stronger lead-lag exogeneity condition holds, namely

$$(11) \qquad \text{(iii)} \qquad E\left[u_{t+j}^{i} z_t'\right] = 0, \qquad \forall j \neq 0 \text{ and } \forall i,$$

then the effects of the shock of interest can be estimated in a single equation regression without controls (LP-IV) (Stock and Watson 2018). The procedure delivers consistent estimates, but it entails a loss of efficiency compared to the SVAR-IV.[24]

Two observations are important to our discussion. First, even with an instrument that fulfills the strict exogeneity condition of equation (10), the impulse response functions to the shock of interest are correctly recovered only if the estimated VAR correctly captures the data generating process. An incorrectly specified VAR, while still allowing for the identification of the impact effects, would produce biased transmission coefficients and hence misspecified impulse response functions.[25] Second, a VAR that does not correctly capture the data generating process will yield residuals that are combinations of current, past, and future shocks. If the instrument violates the lag-exogeneity condition, the impact responses, proportional to the projection coefficients of the VAR residuals on the instrument, will be dependent on the VAR specification.

These two observations provide us with one additional testable implication of the information channel of monetary policy actions. In fact, and importantly, in the presence of information frictions, standard instruments for monetary policy shocks can be contaminated by current but also past macroeconomic shocks. Indeed, a strong implication of information frictions is the violation of the conditions in equations (10)–(11). While the former is not directly testable, the latter is, by looking at the dependence of the estimated impact responses to the changes in the VAR information set. In fact, in this case, not just the shape of the dynamic responses but also the estimated impacts will depend on the VAR specification.

In light of these remarks, a partial explanation for the differences across the specifications in Figures 3 and 4 comes from the fact that even in the presence of a strictly exogenous instrument, an incorrectly specified VAR will still lead to misspecified dynamic responses. In fact, as persuasively observed in Caldara and Herbst (2019), the introduction of variables that proxy for financial conditions (such

[23] Given these conditions, an alternative identification method entails adding the instrument to the set of variables and ordering it first in a recursively identified "hybrid" VAR (see, e.g., Ramey 2016). Results would coincide, provided that the VAR is correctly specified, and hence only contemporaneous shocks affect the residuals ε_t.

[24] An interesting case is that of partial invertibility. In this case, while the monetary policy shocks can be recovered as a linear combination of the VAR innovations, the remaining structural shocks cannot (see Stock and Watson 2018 for a discussion on invertibility and partial invertibility). In such a case, VAR residuals are going to be combinations of the current shocks but also potentially of lags and leads of some of the other structural shocks. It can be shown that also in this case it is possible to correctly estimate the dynamic responses to the monetary policy shock using external instruments, under the condition that the instrument is orthogonal to leads and lags of all the other shocks that enter the VAR residuals (a discussion on this point is in Miranda-Agrippino and Ricco 2018). This is a stronger condition than equation (10) but is less restrictive than equation (11).

[25] The intuition for this is that a VAR be seen as a set of seemingly unrelated regressions. Hence, it is possible to recover the impact effects by adopting an external instrument that is strictly exogenous.

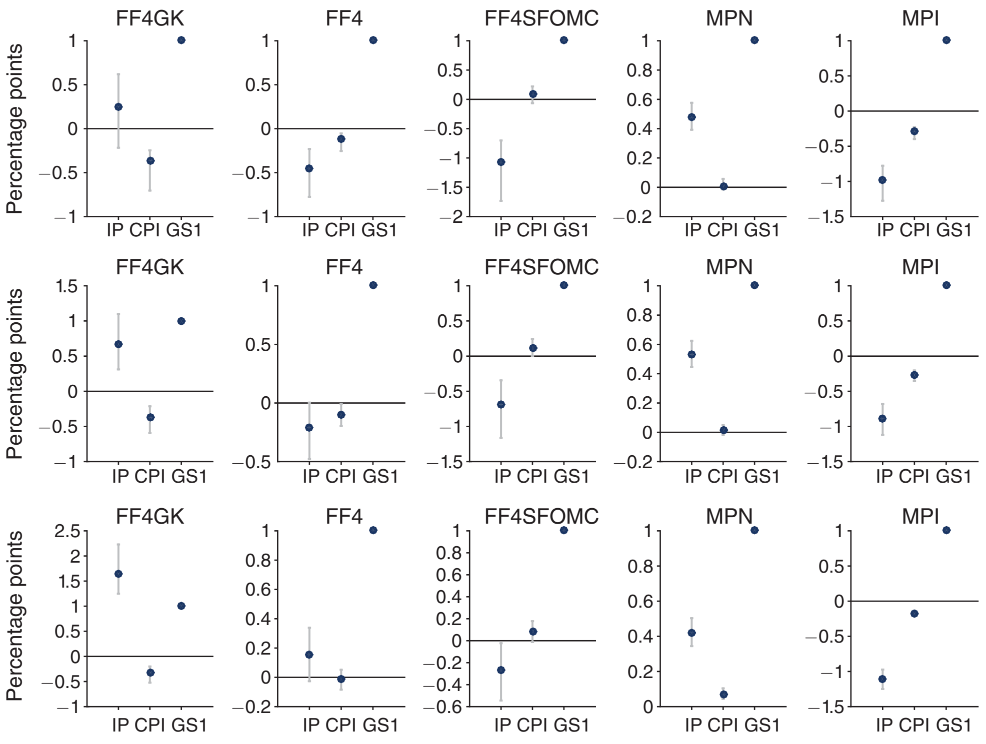

Figure 5. Core Variables: Impact Responses

Notes: Impact responses to a monetary policy shock of core output and price variables. Top panels: VAR(12), 6-variables. Middle panels: VAR(12), 5-variables. Bottom panels: VAR(2), 3-variables. Shock identified with external instruments. From left to right in each row: 1. Gertler and Karadi's (2015) average monthly market surprise; 2. narrative instrument of Romer and Romer (2004); 3. informationally robust MPI; 4. sum of FF4 surprises within the month; 5. FF4 surprises at scheduled FOMC meetings only. The shock is normalized to induce a 100 basis point increase in the 1-year rate. Sample 1979:1–2014:12. Gray bars are 90 percent posterior coverage bands.

as, e.g., the EBP in the first specification) produces overall more convincing responses, at least when using high-frequency instruments. However, the fact that also impact responses can be both counterintuitive and dependent on the VAR specification is primarily driven by contamination of the monetary policy instruments induced by the central bank information channel.

We further explore this issue in Figure 5, where we highlight the estimated impact responses of output and prices as we vary the instrument for identification (across columns in the figure) and the composition and specification of the VAR (across rows in the figure). In each subplot, the impact response of the one-year rate (GS1) is normalized to be equal to one. In each row, from left to right, the instruments used for the identification of monetary policy shocks are the three we use in Figures 3 and 4: Gertler and Karadi's (2015) FF4-based average monthly market surprise, the narrative instrument of Romer and Romer (2004), and our informationally robust MPI. To these we add the sum of FF4 surprises within the month and the FF4 surprises registered around scheduled FOMC meetings only. In the top and middle rows of the figure, impact responses are calculated from the innovations of the VARs of Figure 3 and Figure 4, respectively. In the bottom row of the figure, we magnify the misspecification of the system by estimating a VAR with two lags in the three variables displayed.

Results in Figure 5 provide empirical support to the argument discussed above. Impact responses for different versions of the market-based monetary surprises vary both in magnitude and sign depending on the VAR composition. For example, consider the subplots in the second column (FF4). The impact response of industrial production goes from being negative in the larger VARs to being positive in the smaller system. Similar considerations hold if one restricts the attention to scheduled FOMC meetings only (column 3 of Figure 5): from the top to the bottom rows, the impact response of output shrinks by about two-thirds. It is also worth noticing that this instrument elicits a positive initial reaction of prices, regardless of the VAR specification. Results relative to the average surprises of Gertler and Karadi (2015) and the narrative instrument of Romer and Romer (2004) highlight the instability of impact responses in these cases, in line with what is discussed for Figures 3 and 4. Finally, impact responses estimated using our informationally robust instrument are remarkably stable across the two specifications and do not depend on the inclusion in the VAR of financial variables. The stability of the results relative to the core output and price variables gives us confidence on the exogeneity of our instrument. In the next section, we employ the new instrument to study the propagation of monetary policy disturbances on a large cross section of variables.

The Information Effects.—In Figure 6, we study how macroeconomic and financial variables respond to the "informational" component of the monetary policy surprises, as captured by the fitted component of equation (7), aggregated at monthly frequency. The responses capture the effect of central bank information about the short-term macroeconomic outlook that market participants extract at the time of the announcements.[26] In this VAR, we also include the 10-year Treasury rate, the stock market index, and the effective dollar exchange rate.[27] In the figure, dashed lines are used for the responses to the information component, while solid lines are the responses to a monetary policy shock identified with MPI_t.

In line with our argument, while the uncertainty around the information effects is larger than for the monetary policy shocks—due to the intrinsic uncertainty associated to central bank's forecasts—the difference between the responses elicited by the two shocks is large and strongly significant. While both shocks raise the nominal interest rate by the same amount on impact, the information shock is followed by an economic expansion at business cycle frequency, consistent with the view that a rate increase can signal to market participants that the central bank is expecting a stronger economy going forward. Quantities and prices rise, the stock market rises in value, and credit conditions ease. These results support the view that market participants extract from central bank announcements information on the aggregate

[26] As discussed, the Greenbook projections at the short horizon have the largest predictive power. This is consistent with the maturity of the FF4 futures covering up to three months ahead. In order to extract a proxy for the central bank information while minimizing issues of multicollinearity, we consider the fitted value of equation (7), where we limit the maximum horizon to one quarter ahead.

[27] The sample, lags, and estimation procedure are unchanged.

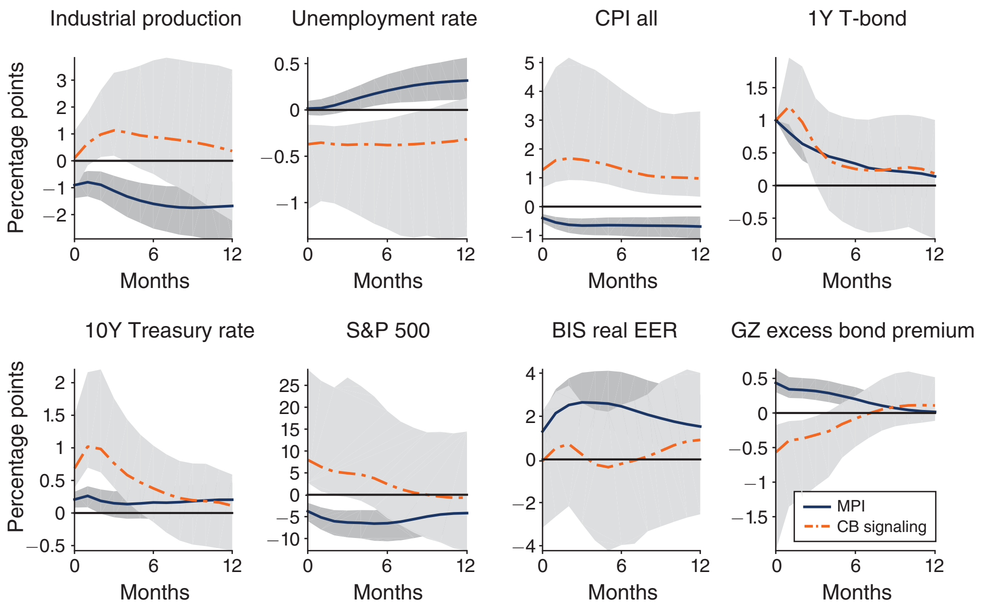

Figure 6. Monetary Policy Shocks versus Information Effects

Notes: Responses to a monetary policy shock identified with MPI_t (solid lines) and to the information component in monetary surprises (fitted component of equation (7), dash-dotted lines). Both shocks are normalized to induce a 100 basis point increase in the 1-year rate on impact. Sample 1979:1–2014:12. Shaded areas are 90 percent posterior coverage bands.

demand shocks to which the central bank is likely to respond. Equivalent conclusions are reached using a different but complementary methodology in Jarociński and Karadi (2020). Monetary policy surprises that contain both monetary policy shocks and demand shocks would blend the two effects reported in the figure and hence produce puzzles.

V. The Transmission of Monetary Disturbances

Monetary policy decisions are thought to affect economic activity and inflation through several channels, collectively known as the transmission mechanism of monetary policy. In this section, we report our empirical results on the effects of monetary policy shocks on a large number of variables and provide evidence compatible with the activation of several of the potential channels that have been discussed in the literature (see, e.g., Mishkin 1996, Bernanke and Gertler 1995 for a review). Monetary policy shocks are identified by using the MPI_t instrument defined in Section III. Results, in the form of dynamic responses and obtained using a VAR(12) estimated with standard macroeconomic priors over the sample 1979:1–2014:12, are presented in Figures 7 to 9. Variables enter the VAR in log levels with the exception of interest rates and spreads. The shock is identified over the sample common to the external instrument (MPI_t) and the VAR innovations and normalized to raise the 1-year rate (policy variable) by 1 percent. Shaded areas are 90 percent posterior coverage bands. The VAR is estimated with Bayesian techniques and standard Normal-Inverse Wishart priors. The tightness of the prior is set as in Giannone, Lenza, and Primiceri (2015).

In line with results shown in previous sections, a contractionary monetary policy shock is unequivocally and significantly recessionary also in larger models (Figure 7). Tight monetary policy depresses real activity and reduces prices. It is worth observing that industrial production drops on impact, and the contraction is larger than what was reported in previous studies. Capacity utilization and inventories both contract, with peak effects often realized within the first year following the shock. The response of these quantities can help explain the sudden drop in industrial production—firms appear to respond to tighter monetary policy by curtailing production while reducing inventory holdings in order to fulfill shipments related to preexisting orders. The labor market is also significantly and negatively affected but with delay. Both the unemployment rate and total hours worked display muted responses on impact. This is suggestive of the presence of frictions in the labor market, such as contractual obligations, which delay the adjustments. Wages decline in a sluggish fashion, but the effect is estimated with large uncertainty. Conversely, the contraction in prices, whether measured using the CPI index or the personal consumption deflator, is more sudden. In line with models of imperfect information and models in which a number of both real and nominal frictions are at play (e.g., Smets and Wouters 2007), prices do not fully adjust on impact but keep sliding over a few months to reach a negative peak of about half a percentage point within the first six months after the shock.

Real income suffers a prolonged contraction that survives for over a year after the shock. Real durable and nondurable consumption rise on impact to contract at medium horizons, albeit not significantly. We explore the response of consumption in more detail at the end of the section.

The shock induces a significant impact rotation of the yield curve whereby for a 1 percent rise in the 1-year rate, we see up to a 50 basis point contraction in the term spread. Both responses are sudden and temporary: the increase in the policy variable dissipates completely within the first two quarters. We explore further the details of the responses of interest rates at different maturities in Figure 8. Here each subplot is horizon-specific, and maturities (in years) are reported on the horizontal axes. All interest rates rise on impact, with responses that are both smaller in magnitude and quicker to revert to trend the higher the maturity. The long end of the yield curve (20-year rate) does not move, in line with what is expected for the effects of a temporary monetary contraction (see also discussion in Romer and Romer 2000, Ellingsen and Soderstrom 2001). All the curve's responses are not significant at the six-month horizon.

To better understand the strong real effects discussed above, particularly in light of the relatively muted movements of the long end of the curve, we investigate the responses of financial and credit variables. The effects reported in Figure 7 are consistent with a deterioration of household wealth working through both a reduction of labor income, and of financial wealth. The decline in financial wealth is likely the product of negative valuation effects triggered by the contraction in asset prices. The reaction of asset prices is spread across different asset classes. The stock market suffers important losses. Housing investment collapses, with peak contractions at the

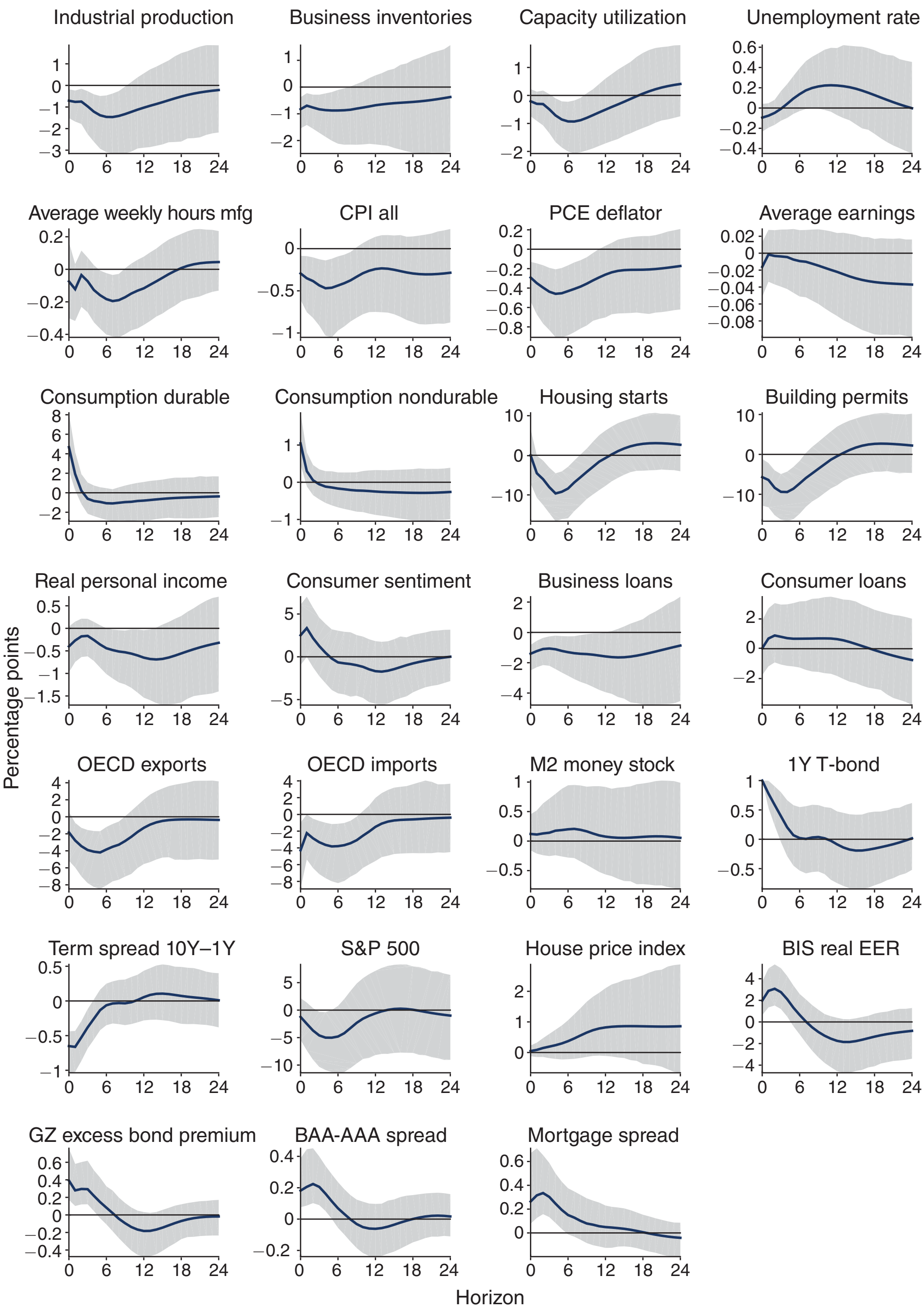

Figure 7. The Effects of Monetary Policy Shocks

Notes: Responses to a contractionary monetary policy shock. Shock identified with the MPI_t series and normalized to induce a 100 basis point increase in the 1-year rate. Sample 1979:7–2012:12 due to data availability (mortgage spread). VAR(12). Shaded areas are 90 percent posterior coverage bands.

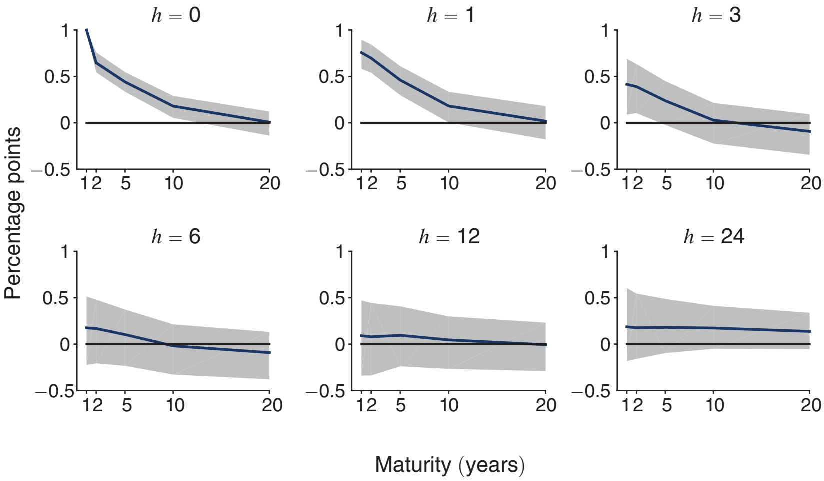

Figure 8. Yield Curve Response to MP Shocks

Notes: Responses to a contractionary monetary policy shock. Shock identified with the MPI_t series and normalized to induce a 100 basis point increase in the 1-year rate. Sample 1979:1–2014:12. VAR(12). Shaded areas are 90 percent posterior coverage bands.

10 percent mark. These effects have a detrimental impact on both equity and assets valuation, making collaterals become more costly.

The strong effects on both real activity and output are likely magnified by the reaction of credit and financial markets, consistently with the "financial accelerator" hypothesis and the existence of a credit channel for monetary policy (Bernanke, Gertler, and Gilchrist 1999). Lending dips significantly, particularly so for businesses. This is consistent with a number of possible mechanisms, all of which find some degree of support. On the one hand, it is the supply of credit that shrinks. Bank lending can contract for several reasons. First, contractionary monetary policy reduces cash flows and increases indirect expenses, with direct effects on the amount of new loans granted. Second, through its effect on asset prices, contractionary policy has a direct valuation effect on lenders' balance sheets. Higher rates mean lower net margins and thus lower profits going forward. Also, the drop in asset prices can imply a reduction in bank capital, which may in turn induce deleveraging in the form of less credit supplied (see Boivin, Kiley, and Mishkin 2010). On the other hand, however, the demand for credit may slow down due to borrowers being less willing to undertake new investment projects. One important reason why this may be the case is that borrowing costs rise. Following the shock, corporate bond spreads and premia (the excess bond premium of Gilchrist and Zakrajšek 2012) both significantly rise on impact and remain high for about half a year. This is consistent with a surge in the external finance premium, that is, the wedge between external (e.g., equity/debt issuance) and internal (e.g., retained earnings) funding costs (see Bernanke and Gertler 1995, Gertler and Karadi 2015). Opposite to what is discussed above, this mechanism operates through the borrowers' balance sheet: the lower the borrower's net worth, the higher the finance premium. Variations in the net worth affect investment and spending decisions, with magnifying effects on borrowing

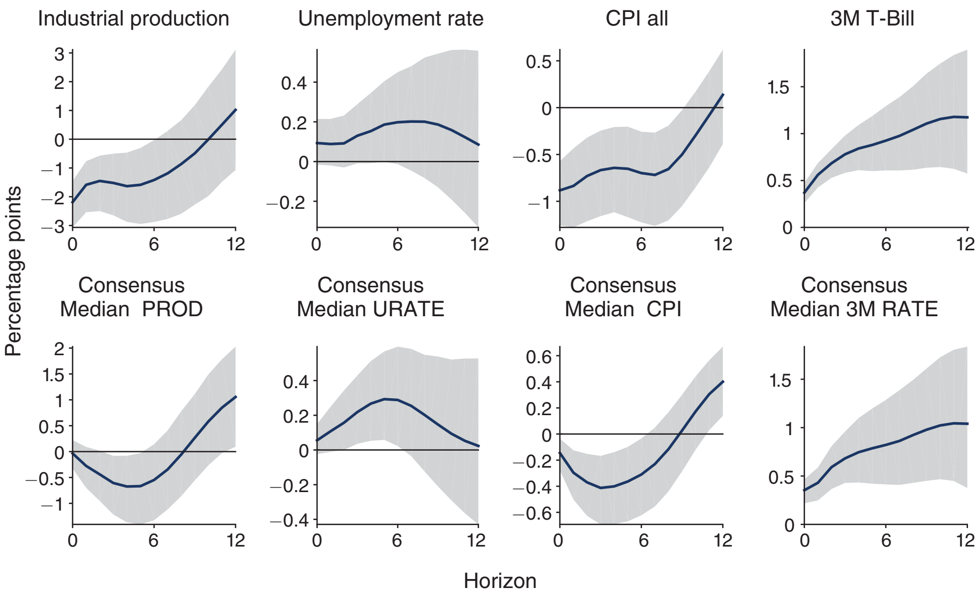

Figure 9. Response of Expectations to MP Shocks

Notes: Responses to a contractionary monetary policy shock. Shock identified with the MPI_t series and normalized to induce a 100 basis point increase in the 1-year rate. Sample 1993:1–2014:12. VAR(12). Shaded areas are 90 percent posterior coverage bands.

costs, real spending, and real activity. The mechanism affects both businesses and households alike. The contraction in housing investments and the increase in mortgage spreads concur to curtail lending to households as well.

After the shock, the dollar appreciates suddenly, and in real terms, against a basket of foreign currencies. This appears to also activate an exchange rate channel. In fact, exports become more costly due to the appreciation and contract as a result. Notwithstanding the stronger purchasing power sustained by the appreciation of the domestic currency, the ensuing recession, accompanied by a contraction of internal demand, also makes imports contract and significantly so.

Finally, we turn to the responses of private sector expectations in Figure 9. As observed in Woodford (2009), modern monetary policy is not simply a matter of controlling overnight interest rates but rather one of shaping market expectations of the forward path of interest rates, inflation, and income. To study how agents' expectations respond to policy changes, we augment a set of variables relevant for the analysis of the standard interest rate channel with Consensus Economics forecast data.[28]

[28] The estimation sample in this case starts in 1993 due to limited availability of the Consensus Economics forecasts,

$$F_t x_{t+12} = \frac{h}{12} F_t x_{t+h} + \frac{12-h}{12} F_t x_{t+12+h},$$

Industrial production and CPI are converted to year-on-year growth rates for ease of comparison, to match the survey units. Agents' median expectations adjust in line with the deteriorating fundamentals. It is important to stress here that this result follows only once the effects of the information channel are appropriately accounted for. Conversely, as documented in Campbell et al. (2012), Campbell et al. (2016), and Nakamura and Steinsson (2018), identifying disturbances using instruments that do not control for such a transfer of information makes expectations adjust in the "wrong" direction, as agents interpret the interest rate move as an endogenous policy reaction to stronger than expected economic developments. Consistent with theory, we find instead that as a result of a contractionary monetary policy shock, agents expect both inflation and output to slow down over time. In particular, forecasts for prices, production, consumption, and investment are all revised downward, while the opposite holds for unemployment forecasts. Interestingly, consistent with the literature on the presence of informational frictions, we find that while the direction of the revision of expectation is in line with a recessionary outlook, forecasters revise their assessment in a sluggish fashion. Notably, while production falls by 4 percent in annual terms, the movement in the forecasts is more gradual over the horizons. Annual CPI inflation drops by 1 percent, while agents revise their forecasts gradually downward. This type of behavior is compatible with information being only partially and slowly processed over time. Conversely, with full information, forecasts should immediately adjust to shocks and by the same amount as the variable being forecasted (see discussion in Coibion and Gorodnichenko 2012).

We conclude this section by providing some additional analysis on the responses of consumption. Figure 10 reports the IRFs of nominal durable and nondurable personal consumption expenditures and of the deflator.[29] Interestingly, nominal nondurable consumption falls on impact and remains lower throughout, indicating that the stickiness in consumption plans may be larger than the stickiness in prices. However, this is not the case for durable goods. Some additional insight is offered by the responses of retail sales of durable goods in Figure 11.[30] Sales of most durable goods contract, with the exception of electronics and appliances and trucks. While not conclusive, this evidence points to a mostly contractionary response of consumption, albeit with some exceptions potentially due to heterogeneity across goods and/or consumers. Two forces may be partly responsible for the "puzzling" responses of electronics and appliances and of trucks. First, stores for electronics may be actively trying to reduce inventory to not hold a stock of good subject to rapid obsolescence. Second, a large fraction of electronics and a decent fraction of intermediate goods used in the production of vehicles are imported. The strengthening of the dollar vis-à-vis other foreign currencies may induce a demand-augmenting

where $F_t x_{t+h}$ is the h-month-ahead median forecast of variable x made at time t. The forecasts produced by the respondents are $\{F_t x_{t+h}, F_t x_{t+12+h}\}$, with horizons $h \in \{1, 2, \ldots, 12\}$ and $h + 12$ months (see Dovern, Fritsche, and Slacalek 2012).

[29] The VAR also includes the index of industrial production, the unemployment rate, the policy rate, and the S&P 500. The sample is 1979:1–2014:12, and the VAR is estimated with 12 lags using standard macroeconomic priors.

[30] This VAR is estimated on a shorter sample starting in 1992 due to data availability and also includes the index of industrial production, the unemployment rate, the policy interest rate, and the S&P 500 index as additional endogenous variables.

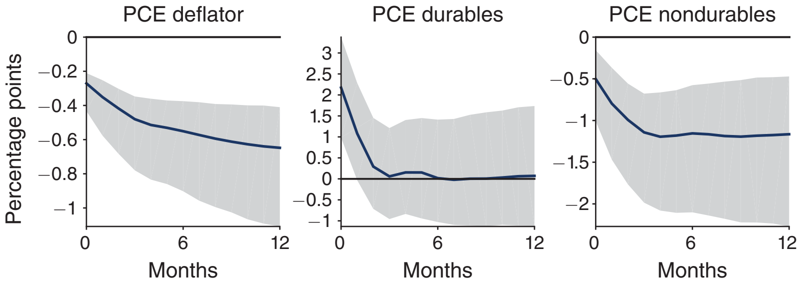

Figure 10. Nominal Consumption Expenditures

Notes: Responses to a contractionary monetary policy shock. Shock identified with the MPI_t series and normalized to induce a 100 basis point increase in the 1-year rate. Sample 1979:1–2014:12. VAR(12). Shaded areas are 90 percent posterior coverage bands.

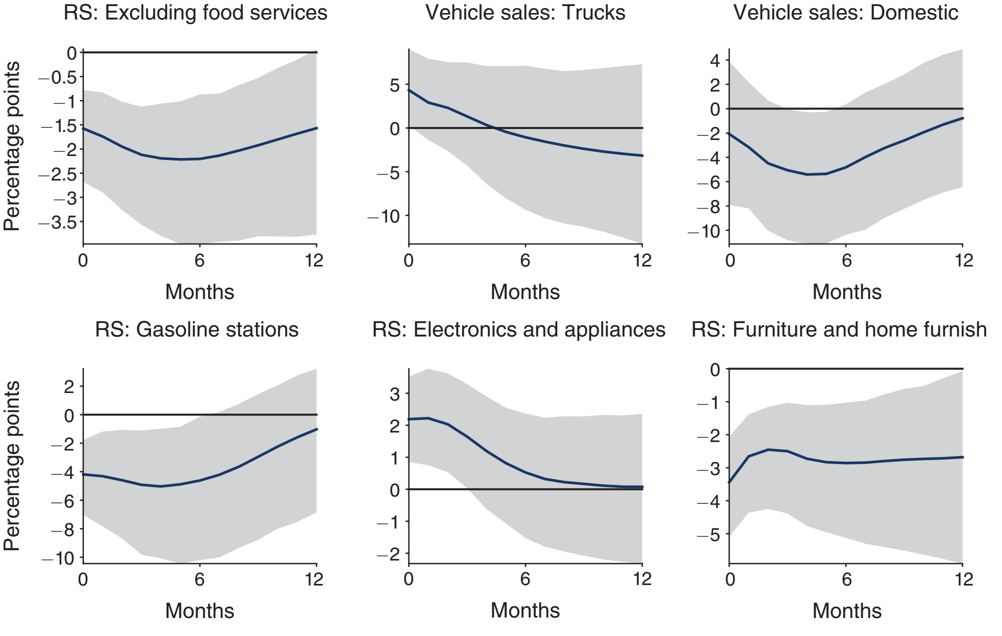

Figure 11. Sales of Durable Goods

Notes: Responses to a contractionary monetary policy shock. Shock identified with the MPI_t series and normalized to induce a 100 basis point increase in the 1-year rate. Sample 1992:1–2014:12 due to data availability (disaggregated sales data). VAR(12). Shaded areas are 90 percent posterior coverage bands.

effect for these goods. This effect is consistent with the PCE deflator falling. While these hypotheses are just speculative, we leave further exploration of these findings to future studies.

VI. Models and Subsamples

In this section, we assess the model and sample dependence of the results reported in the previous sections. This is important in order to gauge how much of the lack of stability of the dynamic responses reported in previous studies can be due to the use of misspecified models or the time variation in the transmission coefficients, besides what is accounted for by the identification strategy. In this respect, we follow the approach of Ramey (2016).

Correct inference on the dynamic effects of monetary policy shocks hinges on the interaction between the identification strategy and the modeling choice. The correct characterization of impulse responses with an external instrument crucially depends (i) on the properties of exogeneity and relevance of the instrument and (ii) on the correct specification of the dynamic model adopted. While condition (i) guarantees that impact responses are correctly recovered (and stable) for any model, condition (ii) is a necessary condition in order to correctly estimate the propagation of the shocks over time (see also discussion in Caldara and Herbst 2019).

Specifically, we assess the fragility of VAR-based results against models built to be resilient to misspecifications of different nature, and we analyze the stability of the dynamic responses across rolling samples. Model misspecifications can arise along several dimensions. First, the information set incorporated in small-size VARs can fail to capture all of the dynamic interactions that are relevant to the propagation of the shock of interest. Second, the lag order of the underlying process may potentially be underestimated. Also, if the disturbances of the underlying data generating process are a moving average process, fitting a low-order or indeed any finite-order VAR may be inadequate. Finally, several possible nonlinearities of different nature may be empirically significant—such as time variation or state dependency of some of the parameters, and nonnegligible higher-order terms.

We compare responses to shocks estimated by using our informationally robust instrument and changing the empirical specification and the samples. In particular, we compare three specifications: (i) a standard Bayesian VAR, (ii) a Local Projection, and (iii) a Bayesian version of the local projection. The rationale for these tests is as follows. From a classical perspective, choosing between iterated VARs and direct methods such as LPs involves a sharp trade-off between bias and estimation variance: the iterated VAR method produces more efficient parameters estimates than the direct method, but it is more prone to bias if the one-step-ahead model is misspecified. Hence, and especially for short samples, VAR methods may produce responses that compound the estimation bias over the horizons, while LP methods—albeit potentially robust to misspecification—are likely to deliver highly imprecise estimates. Both these issues can be the cause of "puzzling" responses and lack of robustness.

This bias-variance trade-off can be accounted for by adopting Bayesian estimation techniques. Following this idea, we develop a Bayesian approach to Local Projection that optimally spans the model space between VAR-based and LP-based impulse responses. In doing so, it helps assessing the source of potentially remaining puzzles that are due to model specifications. BLP results from specifying a (Normal-Inverse Wishart) prior for the local projection coefficients at each horizon, centered around the iterated coefficients of a similarly specified VAR estimated over a presample. The posterior mean of BLP responses takes the form

$$B_{BLP}^{(h)} \propto \left(X'X + \left(\Omega_0^{(h)}\left(\lambda^{(h)}\right)\right)^{-1}\right)^{-1}\left(\left(X'X\right)B_{LP}^{(h)} + \left(\Omega_0^{(h)}\left(\lambda^{(h)}\right)\right)^{-1}B_{VAR}^{h}\right), \tag{12}$$

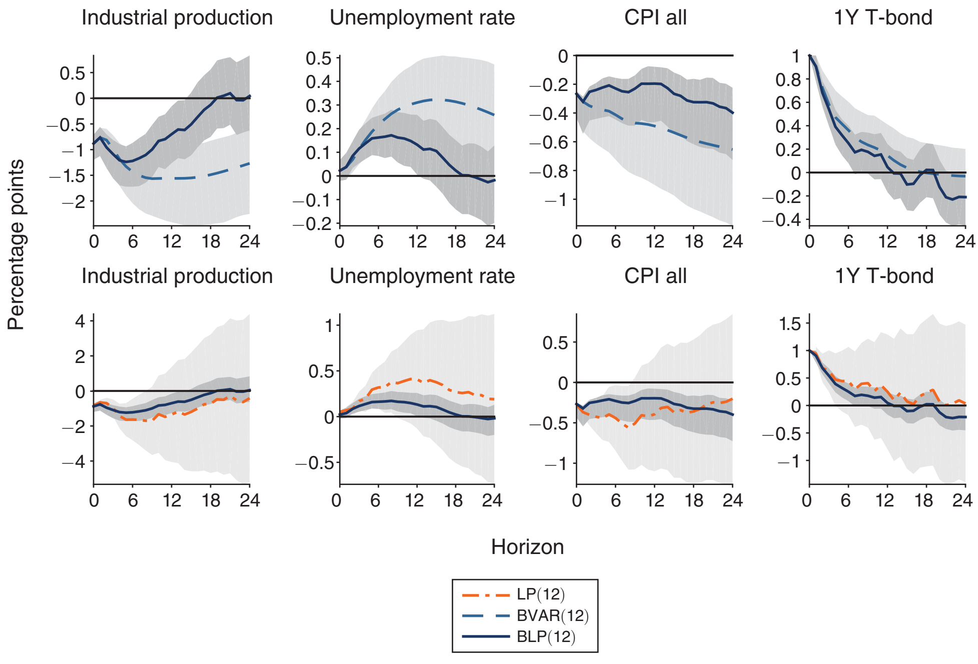

Figure 12. VAR, LP, and BLP Responses

Notes: Top row: VAR (teal, dashed) and BLP (blue, solid) impulse responses. Bottom row: LP (orange, dash-dotted) and BLP (blue, solid) impulse responses. Shaded areas are 90 percent posterior coverage bands.

where $X \equiv (x_{h+2}, \ldots, x_T)'$ and $x_t \equiv (1, y'_{t-h}, \ldots, y'_{t-(h+1)})'$. Intuitively, BLP regularizes LP responses by using priors centered around an iterated VAR while allowing the data structure to select the optimal degree of departure from the priors at each horizon. In fact, extending the argument in Giannone, Lenza, and Primiceri (2015), we treat the tightness of this prior as an additional model parameter for which we specify a prior probability distribution and estimate it at each horizon as the maximizer of the posterior likelihood, in the spirit of hierarchical modeling. This allows us to effectively balance bias and estimation variance at all horizons and therefore solve the trade-off in a fully data-driven way. Details of this approach are provided in the online Appendix and in Miranda-Agrippino and Ricco (2021a).[31]

In Figure 12, we compare the IRFs estimated using the three different empirical settings. In the top row, we compare BLP and VAR responses. The bottom row compares BLP and LP. The variables used are the same as in the baseline set of Figure 4 in Section IV.[32] A few features emerging from this comparison are worth noticing. Overall, over this sample, results are qualitatively consistent across methods: the

[31] This approach has an alternative classical interpretation provided by the theory of "regularization" of statistical regressions (see, for example, Chiuso 2015). Another approach to LP regularization has been proposed more recently in Barnichon and Brownlees (2016). A different Bayesian approach to inference on structural IRFs has been proposed by Plagborg-Møller (2015). Barnichon and Matthes (2014) have propounded a method to estimate IRFs using Gaussian basis functions.

[32] We set the number of lags in both VAR and LP to 12 and use the observations between 1969:1 and 1979:1 as a presample to center the prior for the BLP coefficients. The estimation sample goes from 1979:1 to 2014:12. A detailed description of the method is in the online Appendix.

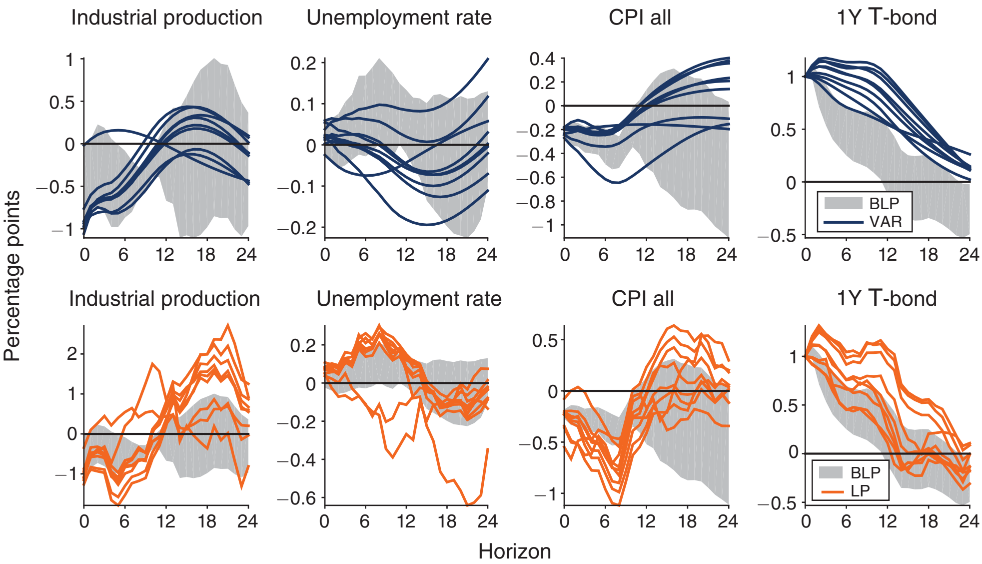

FIGURE 13. VAR, BLP, AND LP RESPONSES ACROSS SUBSAMPLES

Notes: Top row: VAR(12) (blue, solid) and BLP(12) (gray, area) responses. Bottom row: LP(12) (orange, solid) and BLP(12) (gray, area) responses. Subsamples 1982:2006, . . . , 1990:2014.

policy rate returns to equilibrium level within the first two quarters after the shock, and real activity and prices contract under the three modeling alternatives. The length of the sample used, combined with the small size of information set considered, also limits the erratic nature of LPs. Because many sample observations are available at each horizon, the estimates of projection coefficients are relatively well behaved in this instance. However, notwithstanding the relatively long sample available for the analysis, LP responses quickly become nonsignificant after the first few horizons. The width of 90 percent LP confidence bands dwarfs those of BLP responses, which are instead comparable to those of the VAR (BLP responses are the same in the top and bottom rows of the figure). For this set of variables, and over this sample, the shape of LP and VAR responses displayed in Figure 12 is qualitatively similar. VAR responses are, by construction, the smoothest, and have tighter bands. This feature, however, also results in VARs implying stronger and more persistent effects than BLPs (and LPs) do. Conditional on a very similar path for the policy rate response, BLP-IRFs tend to revert to equilibrium faster than VAR-IRFs do and tend to imply richer adjustment dynamics. This may indicate that some of the characteristics of the responses of the VAR may depend on the dynamic restrictions imposed by the iterative structure rather than being genuine features of the data.

We further explore the role that modeling choices play in generating puzzles by focusing on short samples. Figure 13 compares the responses obtained using VAR, LP, and BLP over a set of 24-year subsamples from 1982 to 2014, using our novel instrument. This exercise is helpful to assess how different methods cope with short samples and potentially severely misspecified information sets.[33] The blue lines in the top row of the figure are the VAR responses for each of the subsamples. Similarly, the orange lines in the bottom row are LP responses in each of the subsamples. Conversely, the gray areas in both rows cover all the space occupied by the BLP responses in those same subperiods. We abstract from estimation uncertainty.

A few elements are worth attention. First, the responses of the policy variable are markedly more persistent when estimated with a VAR. In a number of occasions, moreover, the policy rate stays above the 1 percent impact increase for over a year. Second, the reaction of real variables to a monetary contraction is decisively recessionary for BLP. The same does not hold for VAR responses, which, in some cases, lead to puzzling expansionary effects, with production increasing and unemployment decreasing after the shock. Additionally, even when of the "correct" sign, some of the VAR responses for these two variables seem to imply equally puzzling exploding behaviors. Turning the attention to the bottom row of the figure, we see how the erratic nature of LP responses is exacerbated by the small samples used. In particular, we note that LP too can lead to puzzling responses for both production and unemployment in some instances.

In summary, these results show that the responses we obtained in the previous sections after having corrected the monetary policy instrument for the information transfer are robust to different model specifications. However, in small models and for short samples, residual puzzles may still arise because of the limited ability of standard methods to cope with either misspecification (VAR) or estimation uncertainty (LP). Conversely, models that can balance bias and estimation variance, combined with identifications that account for the information structure in the economy, can deliver results that are stable across information sets, samples, and the details of the model specification.

VII. Conclusions

What are the effects of monetary policy? Despite being one of the central questions in macroeconomics, and the numerous theoretical and methodological advances, the discussion on the effects of monetary policy appears to be still surrounded by a substantial degree of uncertainty. In fact, not just the magnitude and the significance but also the sign of the responses of crucial variables such as output and prices depend on the chosen identification strategy, the sample period, the information set considered, and the details of the model specification.

This paper helps rationalizing unstable and puzzling previous results by introducing an identification strategy coherent with the intuitions stemming from models of asymmetric and imperfect information. Results show that following a monetary tightening, economic activity and prices contract, lending cools down, and expectations move in line with fundamentals. Moreover, the currency appreciates, and equity prices fall. Finally, the slope of the yield curve flattens, borrowing costs rise, and so do corporate spreads. These effects are both sizable and persistent, suggesting

[33] For each subsample, the previous ten years are used to calibrate the BLP prior. Hence, this exercise also gives insights of the robustness of BLP to the choice of the presample used for the initialization.

that monetary policy is a powerful tool for both economic stabilization and financial stability. These findings are robust to a number of severe tests.

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