Oil Prices, Gasoline Prices and Inflation Expectations

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It has long been suspected, given the salience of gasoline prices, that fluctuations in gasoline prices shift households' one-year inflation expectations. Assessing this view empirically requires the use of dynamic structural models to quantify the cumulative effect of gasoline price shocks on household inflation expectations at each point in time. We find that, on average, gasoline price shocks account for about one third of the variation in these expectations. The cumulative increase in household inflation expectations from early 2009 to early 2013, in particular, is almost entirely explained by unexpectedly rising gasoline prices. Since much of this effect occurred only toward the end of this period, however, this result does not support the view that the improved fit of the Phillips curve augmented by household inflation expectations during 2009-13 is explained by rising gasoline prices.

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1. Introduction

It is well known that survey data of household inflation expectations may differ systematically from professional inflation forecasts. One of the explanations considered in the literature has been that households' expectations respond excessively to fluctuations in the prices of crude oil and gasoline. For example, Coibion and Gorodnichenko (2015) in a widely cited study make the case that one-year mean household inflation forecasts, as measured by the Michigan Survey of Consumers (MSC), have tracked the price of oil closely with a contemporaneous correlation of 74% between January 2000 and March 2013. Almost all of the short-run volatility of household inflation expectations, according to their analysis, appears explained by changes in the level of the price of oil.[1]

Coibion and Gorodnichenko attribute this result to the high visibility of gasoline prices, which they view as largely determined by the price of oil. They argue that households pay particular attention to gasoline prices when forming their expectations of consumer price inflation. They also make the case that the improved fit of the Phillips curve augmented by household inflation expectations during 2009-13 (compared to a Phillips curve based on professional inflation forecasts) reflects the recovery of gasoline prices starting in early 2009, which raised household inflation expectations, but not professional inflation forecasts. This view has become part of the mainstream in recent years and has been elaborated on in numerous academic and policy studies.[2]

In this paper, we reexamine the empirical support for this conventional wisdom. In the first part of the paper, we show that the static regression evidence and correlations presented

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[1] For example, Coibion and Gorodnichenko (2015, p. 224) write: "Household inflation forecasts have tracked the price of oil extremely closely since the early 2000s, with almost all of the short-run volatility in inflation forecasts corresponding to short-run changes in the level of oil prices. … [T]his feature of the data is not unique to the Great Recession period."

[2] Examples include Elliott, Jackson, Raczko and Roberts-Sklar (2015), Sussman and Zohar (2015), Wong (2015), Binder (2018), Hasenzagl, Pellegrino, Reichlin and Ricco (2018), Conflitti and Cristadoro (2018), and Coibion, Gorodnichenko, Kumar, and Pedemonte (2020).

in Coibion and Gorodnichenko (2015) do not establish that gasoline prices or, for that matter, oil prices drive household inflation expectations. In addition, their evidence is highly sensitive to changes in the estimation period and to reasonable changes in the model specification. Not only is the correlation between household inflation expectations and oil and gasoline prices typically weak, but there is no reason for this correlation to be causal. This does not necessarily mean that there is no causal effect, but it undermines the presumption in the literature based on Coibion and Gorodnichenko's work that much of the variability in inflation expectations is explained by oil and gasoline prices. Our results in the first part of the paper motivate the need for further analysis using alternative econometric approaches and suggest that we need to be open minded about where the evidence leads us.

In the second part of the paper we propose several structural VAR models of the determination of household inflation expectations. Unlike static regression models, structural VAR models allow us to quantify the cumulative effects of nominal gasoline price shocks on inflation expectations at each point in time without imposing strong restrictions on the dynamics of the relationship between inflation expectations and the price of gasoline and without assuming that the gasoline price is strictly exogenous. Estimates of structural VAR models often are sensitive to the identifying assumptions. Our intent in this paper is not to argue that any one of these structural VAR models is the correct specification, but to show that a wide range of alternative identifying assumptions and VAR model specifications produces virtually identical estimates of the response of inflation expectations to nominal gasoline price shocks that are stable over time.

We find that a 10% shock to the nominal price of gasoline increases household inflation expectations by about 0.3 percentage points (at annualized rates) on impact, suggesting that nominal gasoline price shocks do cause inflation expectations to increase. The response of inflation expectations declines rapidly over time, however, and is

indistinguishable from zero after three months. A variance decomposition based on the estimated baseline model reveals that, on average, nominal gasoline price shocks account for only 39% of the variation in household inflation expectations, rather than nearly 100% as the conventional wisdom suggests, with an additional 54% explained by idiosyncratic household expectations shocks and 7% by shocks to consumer prices other than the gasoline price. We discuss the economic interpretation of these shocks from the point of view of more conventional macroeconomic models and show that nominal gasoline price shocks, as defined in the model, in practice will capture shocks to domestic aggregate demand.

We then examine the quantitative importance of nominal gasoline price shocks for the evolution of inflation expectations. We show that this importance varies over time, but there are a number of episodes between 1990 and 2020, in which one-year inflation expectations substantially rose or fell in response to the cumulative effects of gasoline price shocks. In particular, we find that the cumulative increase in household inflation expectations of 1.5 percentage points (at annualized rates) from early 2009 to early 2013 was almost entirely caused by gasoline price shocks, providing support for the conventional wisdom.

It is well documented that the Phillips curve augmented by household inflation expectations provides a better fit for U.S. inflation than a Phillips curve based on professional inflation forecasts. This raises the question of how much of the improved fit of the Phillips curve augmented by household inflation expectations is explained by gasoline price shocks driving up household inflation expectations in 2009-11. The use of the structural VAR approach enables us in the third part of the paper to directly quantify this effect. We demonstrate that, on average, the recovery of gasoline prices starting in early 2009 did not contribute to the improved fit during 2009-13 at all. Even during 2009-2010, only 17% of the gains in accuracy can be attributed to gasoline price shocks, calling into question the prevailing wisdom about the role of gasoline price shocks.

Our work relates to the literature on whether inflation expectations have been successfully anchored by the increased credibility of monetary policy in recent decades (see, e.g., Bernanke 2010; Jorgensen and Lansing 2019). It also relates to a growing literature on how household inflation expectations are determined (see, e.g., Madeira and Zafar 2015; Binder 2018; Angelico and Di Giacomo 2019; Binder and Makridis 2020). In addition, our analysis is related to earlier work on how oil and gasoline price shocks are transmitted to inflation (see, e.g., Kilian 2009; Clark and Terry 2010; Kilian and Lewis 2011; Wong 2015; Conflitti and Luciani 2019). Finally, our analysis contributes to the recent literature on the expectations-augmented Phillips curve (see, e.g., Coibion and Gorodnichenko 2015; Coibion, Gorodnichenko, and Kamdar 2018; Hazennagl et al. 2018).

The remainder of the paper is organized as follows. Section 2 reviews the regression evidence reported in Coibion and Gorodnichenko (2015) and examines its robustness to the estimation period. We draw attention to a number of econometric issues with this type of regression analysis and show that after suitable corrections, there is no statistically significant evidence that the level of oil prices or gasoline prices is correlated with inflation expectations. We also explain why estimates of the correlation between inflation expectations and the price of oil (or gasoline) tend to be unstable over time. Section 3 explains why a structural VAR approach is better suited for quantifying the causal effects of exogenous variation in gasoline prices on inflation expectations. We discuss in depth our preferred structural VAR models, what assumptions are driving our estimates, and how to interpret the shocks in these models. We show that our conclusions are robust to alternative identifying assumptions and provide detailed sensitivity analysis. In addition, we contrast our findings with the analysis of earlier studies of the link between oil prices and inflation expectations such as Wong (2015). Section 4 examines the implications of our analysis for the fit of expectations-augmented Phillips curves. The concluding remarks are in Section 5.

2. How robust is the statistical relationship between the price of oil and inflation expectations?

Coibion and Gorodnichenko (2015) stress that historically the dollar price of a barrel of oil, as measured by the price of West Texas Intermediate (WTI) crude oil, has been highly correlated with the mean of one-year household inflation expectations. The regression estimates reported in their paper, however, are based on regressing the difference between the one-year mean inflation expectation in the Michigan Survey of Consumers (MSC) and the corresponding inflation forecast in the Survey of Professional Forecasters (SPF), $\pi_t^{\text{exp}} - \pi_t^{\text{exp},SPF}$, during the period of 1981.3-2013.1 on the level of the oil price, O_t. As shown in Appendix B, Coibion and Gorodnichenko's premise that SPF inflation forecasts do not respond to the price of oil is not supported by the data, suggesting that we need to focus directly on the correlation between π_t^{exp} and O_t.[3] Consider the static regression model

$$\pi_t^{\text{exp}} = \alpha + \beta O_t + \varepsilon_t. \tag{1}$$

As noted by Coibion and Gorodnichenko, a rejection of $H_0 : \beta = 0$ may be interpreted as a rejection of the hypothesis that these two series are mutually uncorrelated. Inference is based on a one-sided t-test.

There are four concerns with this type of regression. First, the regression is unbalanced in that the regressor is a nonlinear transformation of the log price of oil, which is an I(1) variable, as shown in Appendix C, whereas the dependent variable is I(0). This means that the critical values of the t-test are nonstandard and the conventional N(0,1) critical values used in the literature are invalid (see Stewart 2011).[4] In Appendix C, we discuss how the

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[3] This view is in line with subsequent studies that have focused directly on the relationship between household inflation expectations and the level of the oil price (or the gasoline price) (see, e.g., Elliott et al. 2015; Sussman and Zuhar 2015; Wong 2015; Hazennagl et al. 2018; Conflitti and Luciani 2019; Coibion et al. 2020).

[4] There is a large literature on persistent regressors, including spurious regressions among I(1) variables, cointegrating regressions, and dynamic unbalanced regressions of an I(0) variable on lagged I(1) variables. The analysis of the static unbalanced regression model in Stewart (2011) differs from the analysis of the dynamic unbalanced regression model in Park and Phillips (1988, 1989) and the large literature building on their work.

finite-sample distribution of the test statistic may be approximated under $H_0 : \beta = 0$. Table 1

reports the p-value of the one-sided t-test based on this approximation for alternative

specifications of the regressor.[5] The first column shows that we are unable to reject the null at

the 10% significance level for the original specification (1), with the regressor accounting for

only 9% of the variation in household inflation expectations.

Table 1: Estimates of equations (1) and ($1'$), 1990.1-2020.4

	Level of oil price	Level of gasoline price	Log-level of oil price	Log-level of gasoline price
Correlation with $\pi_t^{\exp}$	29.4%	22.1%	20.2%	14.6%
R^2	8.6%	4.9%	4.1%	2.1%
$\hat{\beta}$	0.008	0.190	0.242	0.256
$t_{\hat{\beta}}$	1.83	1.26	1.25	0.81
p-value	0.102	0.180	0.179	0.274

NOTES: The standard errors underlying the t-statistics are computed based on Newey-West standard errors using the data-based estimator of the truncation lag proposed by Andrews (1991). The nonstandard finite-sample distribution under $H_0 : \beta = 0$ is approximated by simulation, as discussed in Appendix C.

Second, the explicit motivation underlying Coibion and Gorodnichenko's work is that

households are likely to pay particular attention to prices they see more often when

forming their expectations of future inflation. Among consumer prices, the price of

gasoline is particularly salient because consumers are confronted with this price daily, as they

pass by gas stations, so it is natural to suspect that they rely on gasoline prices in forming

their inflation expectations. This argument does not apply to the price of crude oil, however.

Oil is not purchased by retail consumers and most consumers would be at a loss when asked

about the current price of crude oil. This fact suggests that the oil price regressor in equation

(1) should be replaced by the price of gasoline. The second column of Table 1 shows that the

evidence becomes even weaker in this case, illustrating the importance of directly testing the

[5] The use of monthly data facilitates direct comparisons with the evidence in Section 3. As Table B1 shows, estimates based on monthly data closely match those based on the quarterly data. Since Figure A1 suggests the possibility of a structural break in this relationship before about 1990, our analysis focuses on data starting in January 1990. As Table B1 illustrates, including the earlier data would only weaken the relationship of interest.

hypothesis of interest rather than relying on the oil price to approximate the gasoline price.[6]

The R^2 of the regression drops from 9% to 5% and the t-statistic drops from 1.83 to 1.26, with a p-value of 0.18.

Third, even though the gasoline price observed by households is expressed in dollars and cents, this does not mean that households change their inflation expectations proportionately to price changes in cents. The inflation rate is the percent change in the price level. Thus, what matters for inflation is the percent change in individual prices implied by the observed dollar price. A reasonable premise is that a consumer would respond more strongly to a 5 cent increase in the gas price from $1 to $1.05 (implying a 5% increase) than to a 5 cent increase from $4 to $4.05 (implying 1.25% increase). In that case, regressing the dependent variable on the logged regressor, as in

$$\pi_t^{\text{exp}} = \alpha + \beta o_t + \varepsilon_t, \qquad (1')$$

where $o_t = \log(O_t)$, and similarly for the gasoline price would be more reasonable. The last two columns in Table 1 show that in this case, the R^2 drops even further and the p-values are 0.18 for the log oil price regressor and 0.27 for the log gasoline price regressor, respectively. Thus, none of the regression specifications shown allows us to reject the null of no correlation at the 10% significance level, and the evidence is getting weaker, the more realistic the specification.[7]

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[6] This distinction would not matter if nominal gasoline prices were always moving proportionately with nominal oil prices, but there are several reasons why they do not in general. First, it is well known that supply shocks in the gasoline market such as the refinery shutdowns that occur in the wake of hurricanes tend to move oil and gasoline prices in opposite direction, as the demand for crude oil falls and the supply of gasoline falls. Second, even if we restrict attention to the passthrough from the oil price to the gasoline price, the link from oil to gasoline prices is likely to be time-varying. The average cost share of crude oil in producing gasoline has been about one half in recent years, with the cost of marketing, distribution, capital and labor, gasoline taxes and other components accounting for the rest. Not only is there no a priori reason for the cost share of oil to remain constant over time or for the shocks to other cost components to be negligible, but gasoline is co-produced with other fuel products, further loosening the link between oil prices and gasoline prices. In addition, it takes time for crude oil price shocks to be passed through to gasoline prices (see, e.g., Venditti 2013, Chudik and Giorgiadis 2021).

[7] Nor would one expect a strong statistical relationship under the alternative since the dependent variable is I(0), but the regressors appears I(1) (or a nonlinear transformation of an I(1) regressor) based on our diagnostics in

Finally, as shown in Appendix B and D, the correlation estimates in question are highly unstable over time. The same sensitivity is observed in $\hat{\beta}$ which is merely a scaled correlation.[8] This finding is no accident. Focusing on the correlation of inflation expectations with variables that are not stationary (such as the price of oil or the price of gasoline) can be deceiving, because the mean of these prices may differ greatly over time, which renders the correlation estimate erratic across subsamples. Appendix D illustrates the practical relevance of this point based on a simulation experiment.

Given the evidence in Appendix C that o_t is I(1), the problems of nonstandard critical values and unstable correlations may be circumvented by regressing inflation expectations on $\Delta o_t \approx (O_t - O_{t-1})/O_{t-1}$. In that case we are able to reject $H_0 : \beta = 0$ at the 5% significance level, but the R^2 is only 2%. Using the economically more plausible growth rate in the gasoline price allows us to reject the null at the 1% level with an R^2 of 6%. Even the latter result, however, is not supportive of a strong statistical relationship between household inflation expectations and gasoline prices and leaves open the question of whether this relationship is causal.[9]

3. Structural VAR Analysis

The evidence in Section 2 not only suggests that the correlation between gasoline prices and

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Appendix B. Thus, under a nonzero β the dependent variable would become I(1) as well, which is at odds with the observed properties of the dependent variable.

[8] This instability arises, even when extending the estimation period back to 1960 when quarterly household inflation expectations first became available. For example, using quarterly data from 1960Q1 to 2013Q1, the correlation in question is 38%, but for 1960Q1-2020Q1 it drops to -5%.

[9] Coibion and Gorodnichenko (2015) also report estimates of household-level panel regressions of the change in individual household inflation expectations on the growth rate of the price of crude oil. This regression specification is obtained by differencing equation (1'). Like equation (1'), these regressions are unbalanced, as noted by Binder (2018), invalidating conventional inference. In addition, as discussed in Binder (2016), the point estimate reported in Table 5 of Coibion and Gorodnichenko (2015) overstates the effect of a change in oil prices on the change in inflation expectations. Due to a reporting error, a one percentage point increase in oil prices is not associated with a 1.6 percentage point increase in expected inflation, as reported in the original paper, but only with a 0.016 percentage point increase. We do not examine these panel data regressions in this paper, because the household-level evidence has already been re-examined in detail in Binder (2018) who found no evidence that one-year inflation expectations are excessively responsive to gasoline price fluctuations.

household inflation expectations is weak, but it also highlights that static reduced-form regressions are not designed to quantify the causal effects of gasoline price shocks on household inflation expectations, especially if we are interested in quantifying the cumulative effect of gasoline price shocks on inflation expectations at each point in time. We seek to address this concern based on several structural vector autoregressive (VAR) models that disentangle the sources of variation in the price of gasoline, headline inflation and inflation expectations. The common feature of all these models is that we focus on identifying nominal gasoline price shocks. Our approach is consistent with the observation that it is gasoline prices rather than the price of oil that matter for the formation of household expectations. Like the analysis in Coibion and Gorodnichenko (2015), our approach is behavioral in that we seek to measure the response of household inflation expectations to unexpected changes in the nominal price of gasoline. As discussed in Section 3.3, however, our models allow for alternative economic interpretations of this behavioral relationship.

The structural VAR approach has three main advantages compared to static regression analysis. First, it relaxes the dynamic restrictions implicit in static regression models, allowing delayed feedback to inflation expectations. Second, it accounts for the endogeneity of the price of gasoline with respect to domestic inflation variables. Third, the structural VAR approach allows us to quantify the cumulative effect of nominal gasoline price shocks on household inflation expectations at each point in time.

The baseline model is estimated on monthly data starting in 1981.7 and ending in 2020.4. Let $y_t = [rpgas_t, \pi_t, \pi_t^{\text{exp}}]'$, where $rpgas_t$ denotes the log-level of the real gasoline price, π_t is the headline CPI inflation rate, and π_t^{exp} is the Michigan Survey of Consumers measure of households' one-year inflation expectations (see Figure A2). One interpretation of the reduced-form specification is that the headline CPI and the nominal gas price share the same unit root such that the real price of oil, which is a linear combination of these variables,

is stationary. The inflation rate and the inflation expectations are expressed in percent rates, but are not annualized. The real price of gasoline is expressed in logs.

The structural VAR model can be written as $B_0 y_t = B_1 y_{t-1} + ... + B_p y_{t-p} + w_t$, where w_t denotes the mutually uncorrelated i.i.d. structural shocks and B_i, $i = 0,..., p$, represent 3×3 coefficient matrices. The intercept has been dropped for expository purposes. The reduced-form VAR model representation is $y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + u_t$, where $A_i = B_0^{-1} B_i$, $i = 1,..., p$. We set the lag order to a conservative upper bound of 12 lags (see Kilian and Lütkepohl 2017). The model explains variation in the data in terms of the structural shocks $w_t = [w_t^{\text{nominal gasoline price}}, w_t^{\text{core CPI}}, w_t^{\text{idiosyncratic inflation expectation}}]'$.

The gasoline price shock captures innovations in the nominal price of gasoline that are salient to households. In contrast, the shock to the "core CPI" (defined as the CPI excluding the gasoline price) captures innovations to all other consumer prices. Finally, we allow for an idiosyncratic shock to households' inflation expectations that is orthogonal to the first two structural shocks. This shock is designed to capture changes in households' perceptions of future inflation not captured by current prices. An example of such a shock would be a surge in household inflation expectations driven by (perhaps unwarranted) fears about the inflationary impact of fiscal stimulus and quantitative easing not reflected in current consumer prices. The importance of allowing for such idiosyncratic shocks has been emphasized in Madeira and Zafar's (2015) study of household-level inflation expectations data.

The identification of the structural model exploits a combination of sign and zero restrictions on the structural impact multiplier matrix B_0^{-1}, as shown in equation (2). Even though the reduced-form model is expressed in terms of the real price of gasoline, the gasoline price shock we seek to identify is a nominal price shock. A positive nominal

gasoline price shock is assumed to raise the real price of gasoline on impact because the CPI

responds more slowly than the nominal price of gasoline. It is also assumed to raise

household inflation expectations, given the household-level evidence in Binder (2018). The

model does not take a stand on whether consumers expect higher gasoline prices to be

inflationary because they raise the costs of producing goods and services or whether they

think of higher gasoline prices as leading indicators for demand-driven inflationary pressures.

A positive shock to the core CPI raises headline inflation and inflation expectations,

consistent with the evidence in Binder (2018). It lowers the real price of gasoline on impact,

given that the nominal gasoline price does not respond within the month to inflation shocks

(see Kilian and Vega 2011). Finally, a positive shock to idiosyncratic inflation expectations

leaves the real price of gasoline and headline inflation unaffected on impact because

expectations shocks that move actual consumer prices are already captured by the gasoline

and core CPI shocks. Jointly these restrictions imply that

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\begin{pmatrix} u_t^{rpgas} \\ u_t^{\pi} \\ u_t^{\pi^{exp}} \end{pmatrix} = \begin{bmatrix} + & - & 0 \\ + & + & 0 \\ + & + & + \end{bmatrix} \begin{pmatrix} w_t^{\text{nominal gasoline price}} \\ w_t^{\text{core CPI}} \\ w_t^{\text{idiosyncratic inflation expectation}} \end{pmatrix}. \tag{2}
$$

In later sections, we explore alternative identification strategies and model specifications and

show that our results are robust to these changes. We defer further discussion of the economic

interpretation of the structural shocks to Section 3.3.

The model is estimated by Bayesian methods using a uniform-Gaussian-inverse

Wishart prior, as described in Arias, Rubio-Ramirez and Waggoner (2018). The reduced-

form prior is a conventional Minnesota prior with zero mean for the slope parameters. In

Appendix E, we provide further details about the parameter prior and show that this prior is

largely uninformative for the vector of structural impulse responses and is not driving our

empirical results. Having simulated the posterior distribution of the structural impulse

responses, we evaluate the joint distribution of all identified impulse responses under additively separable; absolute loss, as discussed in Inoue and Kilian (2020a).

3.1. How do inflation expectations respond to nominal gasoline price shocks?

Figure 1(a) shows a subset of the impulse responses obtained by minimizing in expectation the loss function. It also shows the implied joint 68% credible sets. The full set of estimates can be found in Appendix F. A positive nominal gasoline price shock causes a persistent appreciation of the real price of gasoline and a sharp and precisely estimated increase in headline inflation that quickly dies out after three months. It also causes a small, but persistent increase in inflation expectations that is precisely estimated for the first three months. There is no evidence that nominal gasoline price shocks permanently affect one-year inflation expectations. As shown in the appendix, a positive shock to the core CPI has negligible effects on inflation expectations and the real price of gasoline, but raises headline inflation for about two months.[10] In contrast, a positive idiosyncratic shock to household inflation expectations raises inflation expectations persistently. It also temporarily raises headline inflation for about one quarter, but that effect is not precisely estimated. The effect on the real price of gasoline is negligible.

The key result in Figure 1 is that a nominal gasoline price shock that raises the nominal price of gas by 10% on impact boosts inflation expectations by 0.3 percentage points at annualized rates within the same month.[11] After accounting for estimation uncertainty, this estimate may be as low as 0.2 and as high as 0.5 percentage points. A common question in the literature is whether the responses of inflation and of inflation expectations to nominal

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[10] Much of the unexpected variation in core CPI prices, as defined in the paper, is likely to come from supply-driven food price shocks, food prices being the most variable and least predictable CPI component apart from gasoline. Since these shocks tend to be caused by temporary supply shortages, one would only expect a modest effect on one-year inflation expectations, but much more pronounced effects on current headline inflation, which is indeed what the impulse estimates indicate.

[11] This estimate is obtained by appropriately scaling $\hat{\theta}_{31,0} / (\hat{\theta}_{11,0} \times 100 + \hat{\theta}_{21,0})$. where $\theta_{jk,h}$ denotes the response of variable j to structural shock k at horizon h.

Figure 1: Impulse response estimates and 68% joint credible sets, 1981.7-2020.4
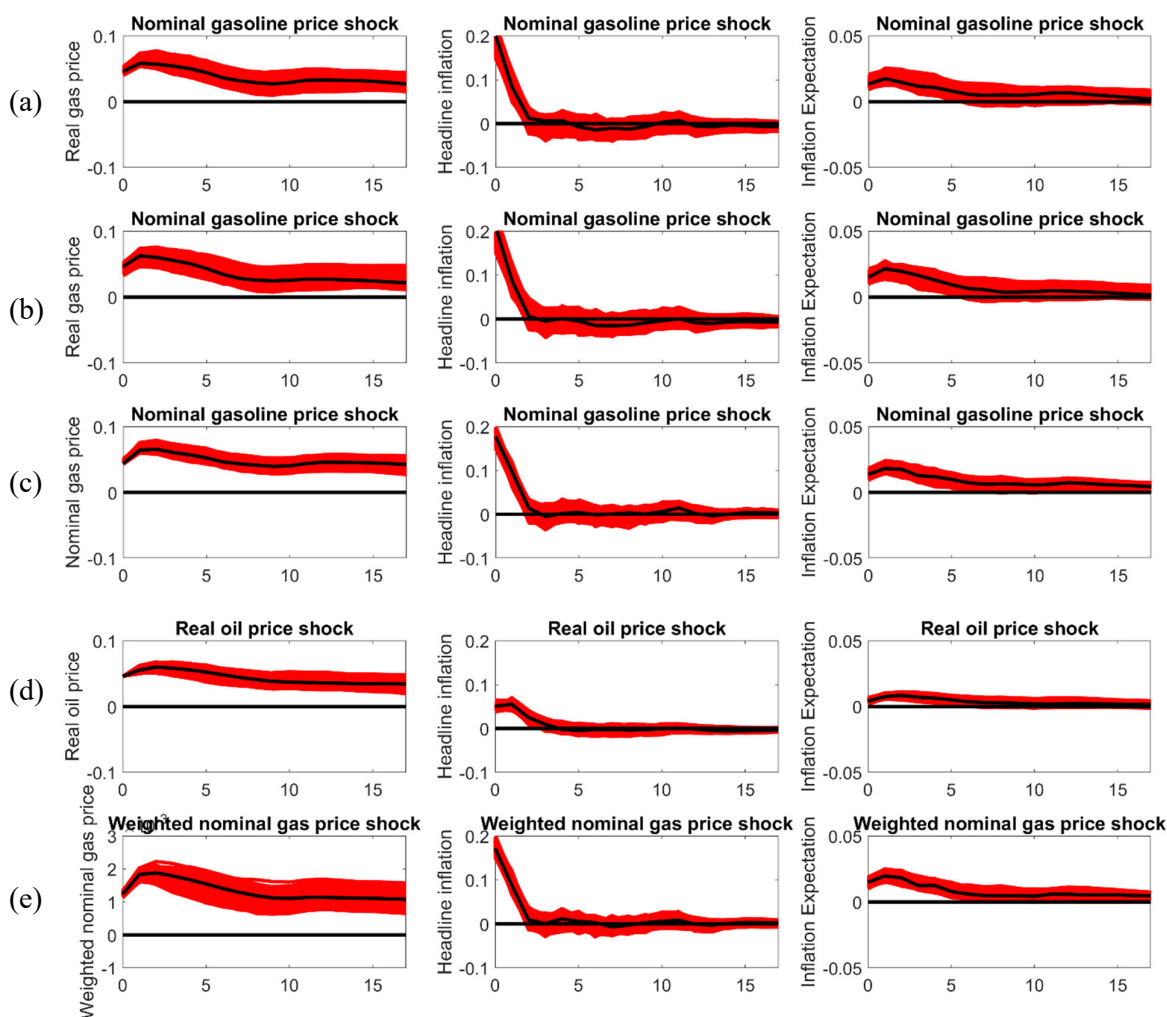
NOTES: The set of impulse responses shown in black is obtained by minimizing the absolute loss function in expectation over the set of admissible structural models, as discussed in Inoue and Kilian (2020a). The responses in the corresponding joint credible set are shown in a lighter shade. Panel (a): Estimate based on baseline model. Panel (b): Estimate based on baseline model after dropping sign restrictions on inflation expectation. Panel (c): Estimate based on alternative partially identified model. Panel (d) Estimate based on Wong's (2015) model, controlling for the scale of the shock and the estimation period. Wong's model is re-estimated and evaluated using the same approach as for the baseline model. Panel (e): Partially identified model based on expenditure-weighted nominal gasoline price shock.

gasoline price shocks are excessive, given the gasoline expenditure weight of 0.028. For

inflation, the answer is straightforward. In the baseline model the response of inflation to a

1% nominal gasoline price shock on impact is 0.0419%. This is somewhat higher than the

effect on headline CPI inflation expected if only the nominal gasoline price moves, even

accounting for estimation error. In other words, there is an additional modest impact response of core price inflation. This type of argument does not work for inflation expectations, however. Anderson, Kellogg, Sallee and Curtin (2011) and Anderson, Kellogg and Sallee (2013) showed that households in the MSC approximately form expectations of future gasoline prices based on a random walk model. This means that, even if the gasoline price goes up today unexpectedly, the expected change in the gasoline price tomorrow is zero. Given this benchmark, households would not expect gasoline price inflation to persist, regardless of the share of gasoline in spending. Put differently, any nonzero response of headline inflation expectations would be "excessive". Thus, the response of household inflation expectations to nominal gasoline price shocks in our model is not unreasonably small.

3.2. How much of the evolution of inflation expectations must be attributed to nominal gasoline price shocks?

We next conduct a counterfactual analysis of how the evolution of household inflation expectations would have differed in the absence of gasoline price shocks. The counterfactual series is constructed by subtracting the cumulative effect of nominal gasoline price shocks shown in Figure F2 in the appendix (expressed as annualized rates) from the actual survey expectations data. Figure 2 shows that one-year household inflation expectations may rise or fall for periods lasting more than one year at a time, when confronted with large and persistent gasoline price movements. In each case, however, these discrepancies ultimately vanish. One example is the period from late 2014 to late 2017, when falling gasoline prices masked a rise in inflation expectations. A similar event is about to unfold at the end of the sample in response to the Covid-19 epidemic. By April 2020, the drop in nominal gasoline prices already accounted for an almost one percentage point gap between actual and counterfactual household inflation expectations. Another example is the late 1990s following

Figure 2: Actual mean one-year inflation expectation in *Michigan Survey of Consumers* and counterfactual series in the absence of nominal gasoline price shocks, 1990.1-2020.4
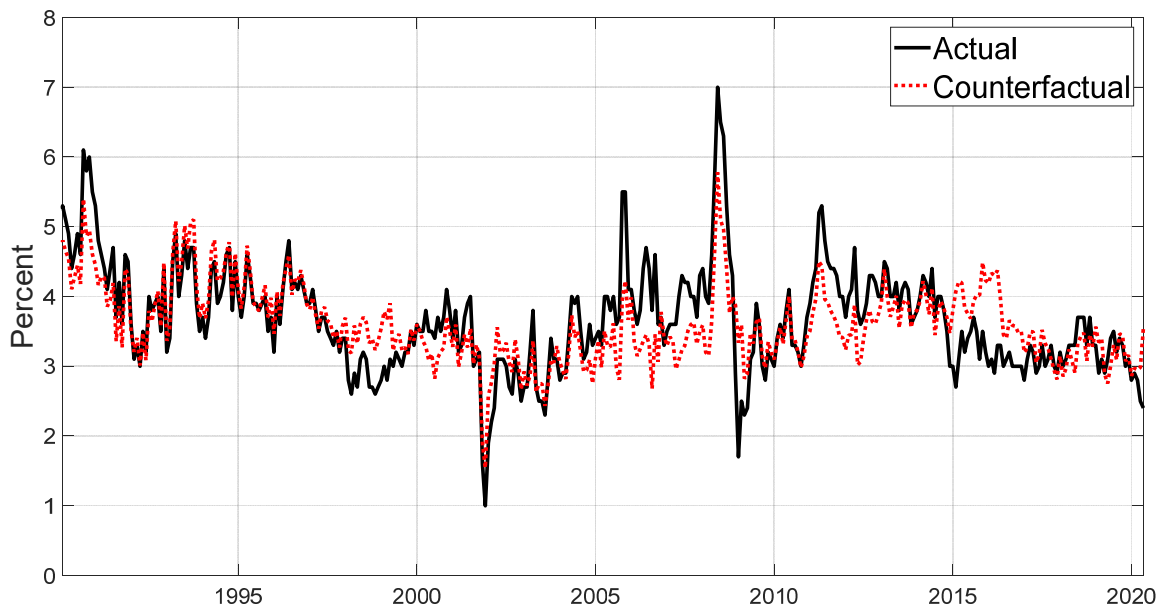
NOTES: The counterfactual time series is obtained by subtracting the cumulative effect of nominal gasoline prices shocks on household inflation expectations, as shown in Figure F2, from the actual data after rescaling the fitted data to represent annualized inflation rates.

the Asian crisis. Periods when inflation expectations were elevated by the cumulative effect of nominal gasoline price shocks, in contrast, include 1990, when Iraq invaded Kuwait, and the period of the Great Surge in the price of oil from 2004 to mid-2008.

Of particular interest is the period of January 2009 to March 2013, which plays a central role in Coibion and Gorodnichenko's (2015) analysis of the Phillips curve. Over this period, household survey inflation expectations increased by 1.5 percentage points (on an annualized basis). Figure 2 implies that in the absence of nominal gasoline price shocks, household inflation expectations would have cumulatively increased by only 0.1 percentage points over this period. Thus, the observed cumulative increase in inflation expectations is largely explained by gasoline price shocks. This does not mean that inflation expectations in general are mostly explained by shocks to gasoline prices, however. A variance decomposition based on the Bayes estimate of the structural VAR model shows that, on

average over the entire estimation period, gasoline price shocks account for only 39% of the variation in household inflation expectations. The most important determinant of inflation expectations on average are idiosyncratic household expectations shocks, which account for 54% of the variation. Shocks to the core CPI explain only 7%.

3.3. What do the structural shocks in the baseline VAR model capture?

Estimates of our behavioral models show robust evidence that households associate unexpected increases in the nominal price of gasoline with higher inflation expectations. While our variance decomposition estimate does not support Coibion and Gorodnichenko's (2015, p. 224) conclusion that nominal gasoline price shocks account for nearly 100% of the variation in one-year inflation expectations, it is still substantial. This result is best understood by interpreting the baseline model (2) from the point of view of a more conventional macroeconomic VAR model. It is widely accepted that positive domestic demand shocks raise inflation, inflation expectations and the real price of gasoline, whereas negative domestic supply shocks raise inflation, raise inflation expectations and lower the real price of gasoline. This means that, all else equal, the core CPI shock in our baseline model (2) can be interpreted as a negative domestic supply shock and the nominal gasoline price shock can be interpreted as positive domestic demand shock. Thus, arguably, the reason why gasoline price shocks are so influential in model (2) compared to the core CPI shock is that they capture domestic demand shocks before they show up in other prices (not unlike commodity prices capturing global demand shifts).

Further insights may be gained by extending the baseline model to include the unemployment rate, ur_t, as a measure of economic slack. This allows us to explicitly identify shocks to domestic aggregate demand. Under reasonable assumptions,

$$
\begin{pmatrix} u_t^{rpgas} \\ u_t^{\pi} \\ u_t^{\pi^{exp}} \\ u_t^{ur} \end{pmatrix} = \begin{bmatrix} + & - & 0 & + \\ + & + & 0 & + \\ + & + & + & + \\ + & + & 0 & - \end{bmatrix} \begin{pmatrix} w_t^{\text{gasoline-specific price}} \\ w_t^{AS} \\ w_t^{\text{idiosyncratic inflation expectation}} \\ w_t^{AD} \end{pmatrix}, \tag{3}
$$

where *AD* and *AS* denote domestic aggregate demand and supply shocks. In this model, one of the key drivers of gasoline prices, the aggregate demand shock, is parsed out. What's left in the first structural shock of model (3) is only the component of gasoline prices that reflects exogenous variation driven by gasoline-specific shocks such as weather-related refinery shutdowns or gasoline-specific demand shocks (say, an unexpected shift in consumer tastes toward SUVs and light trucks). This analysis shows that the nominal gasoline price shock in model (2) captures both the first and fourth structural shock in model (3), but, in practice, gasoline-specific gasoline price shocks are not likely to be as quantitatively important in driving the evolution of gasoline prices as domestic aggregate demand shocks.[12]

The interpretation of gasoline price shocks as primarily capturing demand shocks is in line with existing interpretations of gasoline price shocks in the literature (see, e.g., Sussman and Zohar 2015; Elliott, Jackson, Raczko and Roberts-Sklar 2015).[13] It is also consistent with the view that households extrapolate from the experience of the 1970s and 1980s, when oil and gasoline price fluctuations mainly reflected global and domestic demand pressures (see Barsky and Kilian 2002; Kilian 2008). Indirect support for the latter interpretation is provided by Madeira and Zafar (2015) and Binder and Makridis (2020) who document that this behavioral pattern is more pronounced among households in the Michigan Survey of Consumers who personally experienced the 1970s than among younger households. This

---

[12] The fact that the information set in model (3) includes the unemployment rate in addition makes little difference for the responses to nominal gasoline price shocks, as demonstrated in Appendix G.
[13] A recent example of this mechanism is the global financial crisis of 2008, when a collapse in the global demand for oil lowered U.S. gasoline prices. At the same time, this event reduced the ability of U.S. firms to raise prices, lowering actual inflation, and made households more pessimistic about the future economy, causing them to lower their inflation expectations. This event satisfies all the sign restrictions we imposed in the structural VAR model to identify a nominal gasoline price shock.

view is also in line with a growing literature showing that households' rely on simple rules of thumb for forming inflation expectations rather than trying to understand shifts in demand and supply (e.g., Kamdar 2019; Binder 2020).[14]

3.4. Structural VAR Model Sensitivity Analysis

Before examining the implications of the estimates of the baseline model for the expectations-augmented Phillips curve in Section 4, we scrutinize in more depth the underpinnings of our structural VAR approach. We first examine two alternative strategies for identifying nominal gasoline price shocks that make weaker assumptions than the baseline model. One model relaxes the sign restrictions on the responses of inflation expectations in the baseline model. The other model dispenses with all sign restrictions and relies on alternative exclusion restrictions. We then contrast our findings to earlier work on the relationship between oil prices and inflation expectations such as Wong (2015) and we allow for the time-varying share of gasoline expenditures to affect the feedback from gasoline prices to inflation expectations.[15] Additional sensitivity analysis including an analysis of the temporal stability of the model can be found in Appendix G.

3.4.1. The Role of the Sign Restrictions on Inflation Expectations

The identifying restriction that gasoline price shocks (as well as core CPI shocks) raise

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[14] Some studies suggest that households, when forming their inflation expectations, differentiate between oil price increases driven by global oil supply and oil price increases driven by global demand, building on the work of Kilian (2009) (e.g., Aastveit, Bjørnland and Cross 2021). This idea does not seem plausible. Not only do households not read academic studies, but, even in the academic context, the distinction between oil supply and oil demand shocks was only introduced in Barsky and Kilian (2002) and was only made operational in Kilian (2009). Thus, households could not possibly have been aware of the distinction between oil demand and oil supply shocks during much of our estimation period. Moreover, surely professional inflation forecasters would have been able to exploit this distinction as well as anyone else, yet there is no indication of an increase in the one-year SPF inflation forecast during 2009-13 (see Coibion and Gorodnichenko 2015).

[15] Another potential identification strategy would have been to rely on external instruments. However, as noted by Levin, Lewis and Wolak (2017), "the instrumental variables approaches often adopted in other contexts are rarely used in studies of gasoline [markets] … due to a lack of credible instruments". The closest would be exogenous variation in gasoline tax rates, but that instrument works better in cross-sectional analysis because much of the variation is at the state level. Moreover, this instrument requires dealing with the anticipation of tax changes and gasoline storage (see Coglianese, Davis, Kilian and Stock 2017).

household inflation expectations on impact is based on extraneous household-level evidence in Binder (2018). Imposing these restrictions is not tantamount to assuming that nominal gasoline price shocks have a large effect on inflation expectations because the model allows this effect to be arbitrarily small. The purpose of estimating the model is to quantify the magnitude of this effect. It should be noted, however, that the three structural shocks would remain uniquely identified, even if we dropped these two identifying restrictions such that

$$
\begin{pmatrix} u_t^{rpgas} \\ u_t^{\pi} \\ u_t^{\pi^{exp}} \end{pmatrix} = \begin{bmatrix} + & - & 0 \\ + & + & 0 \\ & & + \end{bmatrix} \begin{pmatrix} w_t^{\text{nominal gasoline price}} \\ w_t^{\text{core CPI}} \\ w_t^{\text{idiosyncratic inflation expectation}} \end{pmatrix}. \tag{2$'$}
$$

Figure 1(b) shows that dropping these sign restrictions leaves unaffected the responses to the nominal gas price shock that are our main interest. A 10% positive nominal gas price shock raises inflation expectations by 0.4 percentage points at annualized rates (with a lower bound of 0.2 and an upper bound of 0.6), similar to the baseline model. This evidence shows that our main results are not driven by the sign restrictions on inflation expectations. Of course, the two sign restrictions in question matter for the overall precision of the estimates.

3.4.2. An Alternative Partially Identified Structural VAR Model

To the extent that we are interested only in the effects of nominal gasoline price shocks, it may be tempting to simply drop all identifying restrictions in model (2) except the sign restrictions associated with the nominal gasoline price shock. As discussed in Appendix H, this approach would not be econometrically sound. A more effective approach is to use a subset of the identifying restrictions in the baseline model to specify a block recursive structural impact multiplier matrix with the growth rate in the nominal price of gasoline (measured in log differences) ordered first, followed by headline inflation and inflation expectations in percent rates, as in model (4). Blank entries in the structural impact multiplier matrix indicate the absence of identifying restrictions.

$$\begin{pmatrix} u_t^{\Delta pgas} \\ u_t^{\pi} \\ u_t^{\pi^{exp}} \end{pmatrix} = \begin{bmatrix} + & 0 & 0 \\ & & \\ & & \end{bmatrix} \begin{pmatrix} w_t^{\text{nominal gasoline price}} \\ w_t^2 \\ w_t^3 \end{pmatrix}. \tag{4}$$

As before, the focus is on identifying the nominal gasoline price shock. The remaining shocks are not explicitly identified and hence are not labelled. This block recursive structure is consistent with evidence in Kilian and Vega (2011) that the nominal price of gasoline is predetermined with respect to inflation news, which was also used in specifying the baseline model.[16]

This specification is consistent with the baseline model in that the nominal price of gasoline in model (2) is implicitly treated as a unit root process, which is why this variable is expressed in log differences in model (4). One difference from our baseline model is that this alternative specification treats the real price of gasoline as I(1), whereas the analysis of inflation expectations in the baseline model does not take a stand on whether the real price of gasoline is I(0) or I(1). Nevertheless, the responses in Figure 1(c) show a very similar pattern to those for the baseline model. The implied response of inflation expectations to a 10% nominal gasoline price shock is 0.4 percentage points at annualized rates. The evolution of the cumulative effect of gasoline price shocks on household inflation expectations is also similar to the baseline model. For example, the cumulative effect from 2009.1 to 2013.3 is 1.6 percentage points compared with the 1.5 percentage point increase in annualized household inflation expectations, confirming that essentially all of the increase in inflation expectations during that episode was driven by nominal gasoline price shocks.

3.4.3. Comparison with the structural VAR Model in Wong (2015)

An important question is how our impulse response estimates differ from those in earlier

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[16] Since the impact response of the first dependent variable is identical whether this response is expressed in log-levels or log-differences, the structural shock may be interpreted as a shock to the log level of the nominal price of gasoline, as in the baseline model.

studies on the link between oil prices and inflation expectations such as Wong (2015). Wong's model is partially identified with the log real price of oil ordered first in a block recursive model. The second block contains inflation and inflation expectations. The key difference is that Wong studied the response of inflation expectations to a real oil price shock, whereas we identify a nominal gasoline price shock. As discussed earlier, it is the latter shock that matters for answering the questions raised in Coibion and Gorodnichenko (2015). We already showed in section 2 that the reduced-form regressions are highly sensitive to the distinction between oil and gasoline prices. This distinction is equally important for impulse response analysis in structural VAR models. Figure 1(d) shows impulse response estimates based on re-estimating Wong's model on monthly data for 1981.7-2020.4. The estimates from Wong's model have been rescaled to match the impact response of the real price of gasoline in our baseline model. The Bayes estimate of the impulse responses in Wong's model look noticeably different from our estimates in Figure 1(c). Although the response function of the real price of oil shows a similar pattern, the magnitude of the impact response of headline inflation is four times as large in the baseline model as in Wong's model. Moreover, the latter response peaks with a delay rather than on impact. Perhaps the single most important difference is that the effect on inflation expectations is much larger in the baseline model than in Wong's model. We conclude that Wong's model does not speak directly to the issues of interest in our paper.

3.4.4. Accounting for the Time-Varying Gasoline Expenditure Share

The average expenditure share for gasoline and other motor fuel in total PCE expenditures for 1981.7-2020.4 is 2.8%, but there has been some variation in that share over time (see Figure A3). A priori it is not clear whether the response of consumers depends on the expenditure share of gasoline or not. The concern is that consumers' inflation expectations may be more sensitive to gasoline price shocks when that share is high, in which case the baseline model

would be misspecified. A natural way of addressing this concern is to weight the growth rate of the nominal gasoline price in the partially identified structural VAR model of Section 3.4.2 by the gasoline expenditure share, building on the approach of Edelstein and Kilian (2009). Figure 1(e) shows that redefining the first VAR variable in this manner has little effect on the responses of headline inflation and inflation expectations. Moreover, the plot of the counterfactual implies that the expenditure share-weighted nominal gasoline price shock explains 1.4 percentage points of the 1.5 percentage point cumulative increase in household inflation expectations during 2009.1-2013.3, much like the unweighted shock in the baseline model.

4. Implications for the Phillips Curve

Coibion and Gorodnichenko (2015) make the case that MSC household inflation expectations are likely to be a better proxy for firms' inflation expectations than professional inflation forecasts from the SPF. They suggest that the use of household inflation forecasts as a measure of expectations in the Phillips curve improves the fit of this curve and can account, in particular, for the missing disinflation during the Great Recession. Coibion and Gorodnichenko (2015, p. 224) argue that the rise in oil and gasoline prices in early 2009 "can account for *all* of the rise in household inflation expectations relative to those of professional forecasters" during 2009-2011 and hence for the improved fit of the Phillips curve during 2009-13.

Our structural VAR approach is particularly well suited for assessing the empirical support for this argument because it allows us to compute the counterfactual path of household inflation expectations in the absence of nominal gasoline price shocks. Our approach to evaluating the Phillips curve differs from and complements the analysis in Coibion and Gorodnichenko (2015). Whereas they asked whether the use of household expectations improves the fit of the expectations-augmented Phillips curve compared to using

SPF inflation forecasts, with all differences in fit being attributed to gasoline price shocks, we directly quantify to what extent conditioning on gasoline price shocks improves the fit of the Phillips curve during this time period.

We start by fitting an expectations-augmented Phillips curves of the form

$$\pi_t = \alpha + \pi_t^{\text{exp}} + \beta gap_t + \varepsilon_t \tag{5}$$

to quarterly data for 1981.3-2007.3, where gap_t is the difference between the U.S. unemployment rate and the short-run natural rate of unemployment, as constructed by the Congressional Budget Office, and π_t^{exp} is the one-year mean household inflation expectations in the MSC. Alternatively, this expectation is replaced by the one-year SPF inflation forecast.[17] Figure 3 plots the actual annualized inflation rate along with the inflation rate implied by equation (5) based on the SPF, the MSC, and the quarterly average of the counterfactual path of the MSC expectations evaluated at the MSC coefficients.

Figure 3 shows, first, that the fit of the Phillips curve evaluated under the counterfactual is not even close to that of the Phillips curve based on the SPF inflation forecast, undermining the conventional wisdom that the difference between these expectations measures is explained by gasoline price shocks. Second, the differences between the Phillips curves evaluated under the actual household expectations and under the counterfactual expectations tends to be modest at best and concentrated toward the end of the evaluation period. This finding is consistent with the evolution of the spread between actual and counterfactual expectations in Figure 2. Although we confirmed earlier that virtually all of the cumulative 1.5 percentage point increase in inflation expectations from 2009.1 to 2013.1 is explained by gasoline price shocks, this statistic obscures that much of this increase occurred only late in this interval rather than in 2009 or 2010. Hence, the fit of the Phillips

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[17] Essentially identical results are obtained when replacing gap_t in the Phillips curve by the unemployment rate.

Figure 3: Fit of alternative expectations-augmented Phillips curves
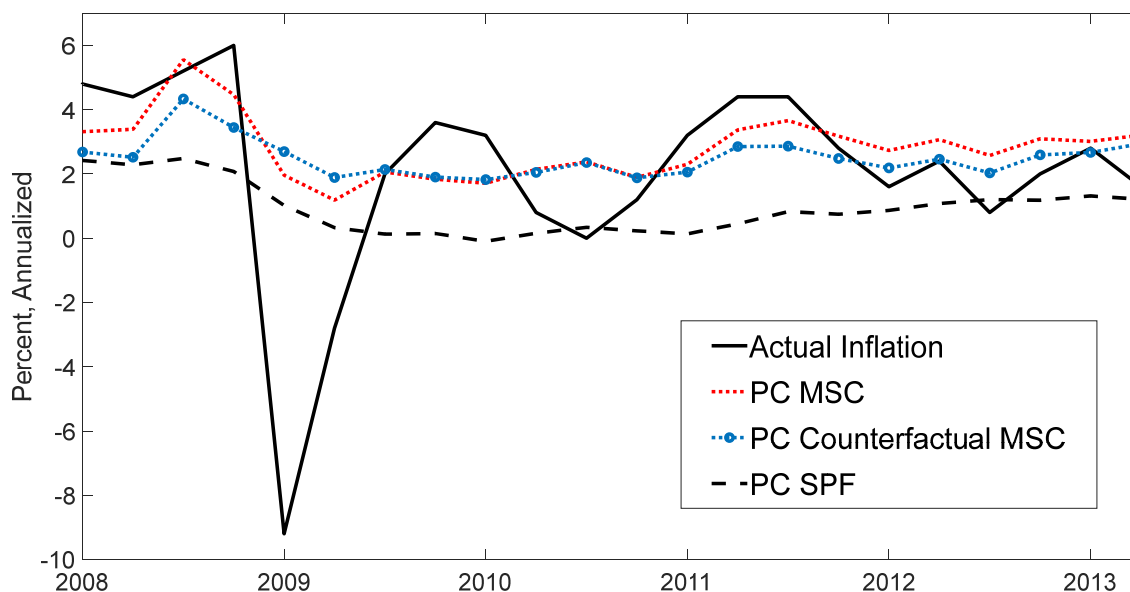
NOTES: Based on OLS estimates of the expectations-augmented Phillips curve on quarterly data for 1981.3-2007.3. The counterfactual is based on the baseline structural VAR estimate of how inflation expectations would have evolved in the absence of nominal gasoline price shocks.

curve under actual and counterfactual MSC expectations largely coincides in 2009 and 2010.

We are interested in how well each specification approximates the actual inflation rate, especially starting in 2009.1. Table 2 reports the average absolute deviation of the fitted values from the actual inflation rate for selected periods. The lower the value, the better the fit. Overall, the MSC expectations measure with an average absolute error of 1.7 percentage points provides a better fit for 2007.4-2013.1 than the SPF forecast. This is also true for every subperiod shown in Table 2. This result does not necessarily mean that it is the gasoline price shocks that make the MSC specification more accurate. A direct test of this part of the conventional wisdom is to evaluate the Phillips curve fit under the counterfactual MSC measure that removes the cumulative effect of gasoline price shocks at each point in time. Table 2 shows that to the extent that the use of MSC inflation expectations improves the fit of the Phillips curve during 2009.1-2010.4, only 17% of this improvement is caused by gasoline

Table 2: Fit of the expectations-augmented Phillips curve under absolute loss

	2007.4-2008.4	2009.1-2010.4	2011.1-2013.1	2009.1-2013.1	2007.4-2013.1
SPF	4.3	2.1	1.6	1.8	2.4
MSC	**3.1**	**1.6**	1.0	1.2	**1.7**
Counterfactual[a]	3.9	1.7	**0.8**	**1.2**	1.8

NOTES: Boldface indicates the Phillips curve model with the best fit for each period. The units are percentage points of annualized inflation.
[a] Counterfactual MSC expectation constructed from baseline structural VAR model in the absence of nominal gasoline price shocks.

price shocks.[18] In contrast, ignoring gasoline price shocks after 2010 actually would have improved the fit of the MSC augmented Phillips curve by 15%, intuitively because actual inflation rates had declined by then. On average over the period 2009.1-2013.1, the PC-Counterfactual MSC specification is marginally more accurate than the PC-MSC specification. Thus, on average, gasoline price shocks contributed nothing to the improved fit of the PC-MSC curve over this period and very little, if we restrict attention to 2009 and 2010.

Table 2 shows that there is little support for the conventional wisdom that the rise in household inflation expectations driven by the unexpected rise in gasoline prices starting in 2009 explains why the U.S. economy did not experience disinflation after the financial crisis. Our evidence shows that the transmission of gasoline price shocks to inflation expectations was much more sluggish than assumed in the conventional wisdom. This sluggishness is captured by the structural VAR model, but not by static regressions. Although gasoline price shocks did have noticeable cumulative effects on inflation expectations, as shown in Section 3, most of these changes occurred long after the gasoline price recovery of 2009, not when conventional wisdom says they did. It certainly remains true that the use of household inflation expectations improves the fit of the Phillips curve for this period, but our analysis

---

[18] This estimate is obtained by dividing the difference in fit between the PC MSC and PC Counterfactual MSC specification in Table 2 by the difference in fit between the PC MSC and PC SPF specification.

suggests that the difference between household and professional inflation forecasts must have a reason other than households' responsiveness to gasoline price shocks.

5. Concluding Remarks

The conventional wisdom that inflation expectations respond to the nominal price of oil (or the price of gasoline) is based on estimates of static reduced-form regressions and correlations. We showed that this evidence must be interpreted with caution. We not only demonstrated that the correlation between gasoline prices and household inflation expectations is weak, but made the case that static reduced-form regressions are not the appropriate tool for quantifying the causal effects of gasoline price shocks on inflation expectations, especially if the objective is to quantify the cumulative effect of these shocks during specific historical periods.

We provided robust evidence based on several alternative structural VAR models that nominal gasoline price shocks indeed contribute to one-year household inflation expectations, but not as much as commonly believed. On average, nominal gasoline price shocks account for only 39% of the variation in household inflation expectations rather than nearly 100%, as suggested in earlier research. Even this share may seem large to some readers. We showed that the seemingly large explanatory power of gasoline price shocks compared to shocks to other consumer prices may be explained by the fact that gasoline price shocks reflect broader demand-driven inflationary pressures before they become apparent in other consumer prices.

The relative importance of gasoline price shocks for household inflation expectations varies over time. We identified several episodes in recent decades, when household inflation expectations rose or fell substantially in response to nominal gasoline price shocks. Notably, our analysis supports the view that the cumulative rise in household inflation expectations from early 2009 to early 2013 can be almost entirely explained by the increase in gasoline prices over this period. Since much of this effect occurred only toward the end of this period,

however, this result does not support the view that the improved fit of the Phillips curve augmented by household inflation expectations between 2009 and 2013 is explained by rising gasoline prices. Although it is true that the use of household inflation expectations improves the fit of the Phillips curve during this period, our analysis suggests that the difference between household and professional inflation forecasts must have a reason other than household's responsiveness to gasoline price shocks.

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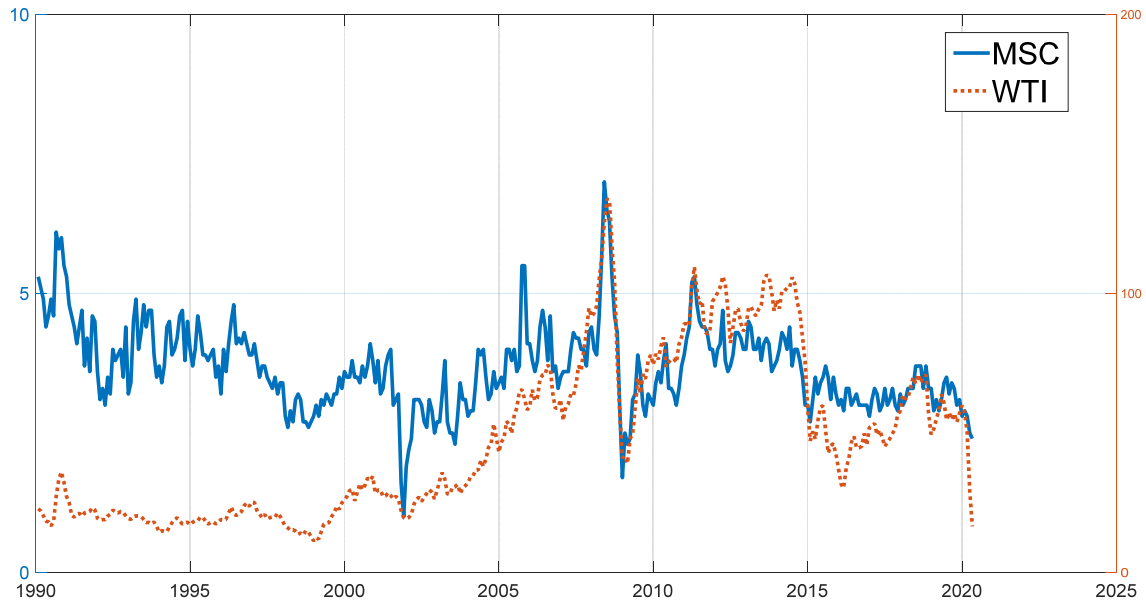
Appendices:
Oil Prices, Gasoline Prices and Inflation Expectations:

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Appendix A: Data Plots

Figure A1: Household inflation expectations and the price of oil: 1990.1-2020.4

NOTES: The oil price is the spot price for WTI crude oil reported by the EIA. MSC denotes the Michigan Survey of Consumers mean one-year inflation expectation.

Figure A2: Indicators used in the VAR analysis, 1981.7-2020.4
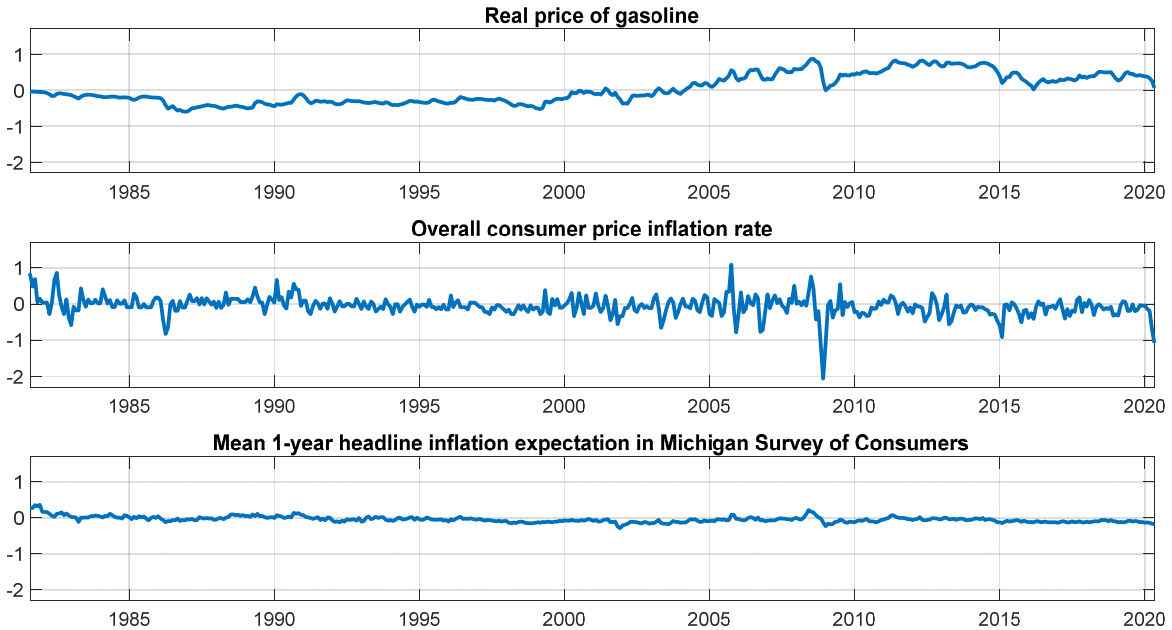
NOTES: The inflation rates are expressed in monthly percent changes. The real price of gasoline has been expressed in logs. All data have been demeaned.

Figure A3: Gasoline expenditure share, 1981.7-2020.4
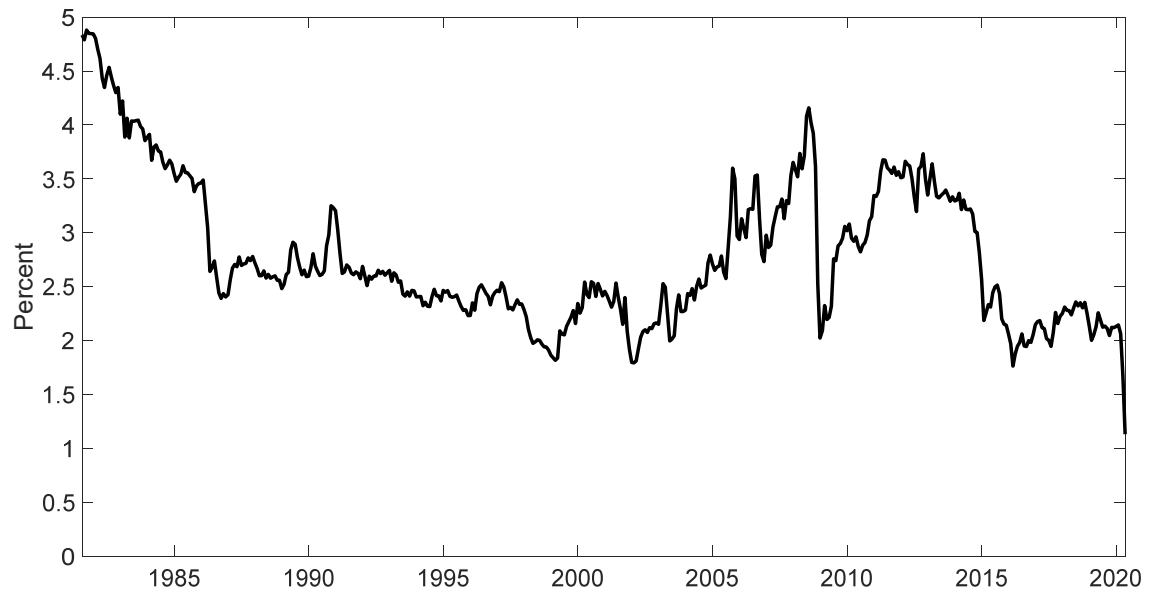
NOTES: Based on BEA data for total nominal consumer expenditures and expenditures on gasoline and other motor fuel.

Appendix B: How Robust is the Evidence in Coibion and Gorodnichenko (2015) on the Correlation between Oil Prices and Inflation Expectations

Coibion and Gorodnichenko (2015) stress that historically the dollar price of a barrel of oil, as measured by the price of West Texas Intermediate (WTI) crude oil, has been highly correlated with one-year household inflation expectations in the aggregate. The estimate reported in their paper, however, is based on regressing the difference between the one-year mean inflation expectation in the Michigan Survey of Consumers (MSCO and the corresponding inflation forecast in the Survey of Professional Forecasters (SPF), $\pi_t^{exp} - \pi_t^{exp,SPF}$, during the period of 1981.3-2013.1 on the level of the oil price, O_t. Coibion and Gorodnichenko do not report estimates of regressions of π_t^{exp} on O_t. They only report a 74% correlation between π_t^{exp} and O_t for the period of 2000.1-2013.1 and a plot of these two series from 1990.1 to 2013.1.

Table 1 provides a comprehensive overview of the key facts. The first column is based on the estimation period used in Coibion and Gorodnichenko's (2015) Table 4. The second column is based on the time frame utilized in their time series plot. The third column focuses on the period for which Coibion and Gorodnichenko report the correlation between the oil price and inflation expectations. Finally, the last two columns correspond to the first two columns, except that the estimation period has been extended to early 2020.

The first panel of Table 1 shows that the correlation between $\pi_t^{exp} - \pi_t^{exp,SPF}$ and O_t is robust across estimation periods. This evidence, however, does not address the question of how correlated π_t^{exp} and O_t are. The second panel shows that we can replicate the 74% correlation between π_t^{exp} and O_t highlighted by Coibion and Gorodnichenko for 2000.1-2013.1, but that correlation becomes much weaker when estimation starts in 1990.1 and all but vanishes when estimation starts in 1981.3. Moreover, the slope coefficient drops to 0.004, the t-statistic drops to 1 and the R^2 to 1.3% in the latter case. In no case is there evidence of a tight link between the oil price and household inflation expectations, except for the 2000.1-2013.1 period.

The near-zero coefficient in the regression of π_t^{exp} on O_t raises the question of what is driving the comparatively high slope coefficient of 0.024 in the regression of $\pi_t^{exp} - \pi_t^{exp,SPF}$ on O_t in column (1). The third panel in Table B1 shows that this estimate is driven by the negative slope coefficient in the regression of $\pi_t^{exp,SPF}$ on O_t, which is -0.020 with a t-statistic of -4.2. This evidence is difficult to reconcile with the argument that households adjust their inflation forecasts more strongly in response to oil price changes than professional forecasters because of the salience of gasoline prices to consumers. Table B1 directly contradicts the conclusion in Coibion and Gorodnichenko (2015) that "household forecasts respond more rapidly to oil price movements than professional forecasters". Not only is there no evidence of households adjusting at all, but the adjustment of professional forecasters is in the opposite direction from what one would have expected from households.

As the last panel in Table B1 shows, the often low and sometimes erratic correlation between household inflation expectations and the price of oil is not an artifact of using quarterly data. Much the same result holds in monthly data.

Our evidence demonstrates that it is essential to study the relationship between the price of oil and household inflation expectations directly rather than expressing these expectations relative to the SPF inflation forecast.

Table B1: An overview of the regression evidence

Quarterly Regressions for Inflation Expectations Spread					
Dependent variable: $\pi_t^{\text{exp}} - \pi_t^{\text{exp},SPF}$	1981.3-2013.1	1990.1-2013.1	2000.1-2013.1	1981.3-2020.1	1990.1-2020.1
$corr(\pi_t^{\text{exp}} - \pi_t^{\text{exp},SPF}, O_t)$	77.9%	85.1%	84.6%	78.6%	82.8%
$\hat{\beta}$	0.024	0.021	0.022	0.022	0.019
$\hat{t}_\beta$	12.91	15.71	10.94	10.83	11.80
R^2	60.7%	72.4%	71.6%	61.8%	68.5%
Quarterly Regressions for Household Inflation Expectations					
Dependent variable: π_t^{exp}	1981.3-2013.1	1990.1-2013.1	2000.1-2013.1	1981.3-2020.1	1990.1-2020.1
$corr(\pi_t^{\text{exp}}, O_t)$	11.4%	35.0%	74.4%	3.7%	29.3%
$\hat{\beta}$	0.004	0.009	0.021	0.001	0.007
$\hat{t}_\beta$	1.01	2.16	5.38	0.29	1.68
R^2	1.3%	12.3%	55.3%	0.1%	8.6%
Quarterly Regressions for SPF Inflation Expectations					
Dependent variable: $\pi_t^{\text{exp},SPF}$	1981.3-2013.1	1990.1-2013.1	2000.1-2013.1	1981.3-2020.1	1990.1-2020.1
$corr(\pi_t^{\text{exp},SPF}, O_t)$	-42.2%	-51.5%	-14.1%	-42.8%	-54.5%
$\hat{\beta}$	-0.020	-0.012	-0.002	-0.021	-0.012
$\hat{t}_\beta$	-4.20	-3.08	-0.54	-4.51	-3.29
R^2	17.8%	26.5%	1.93%	22.8%	29.7%
Monthly Regressions for Household Inflation Expectations					
Dependent variable: π_t^{exp}	1981.7-2013.3	1990.1-2013.3	2000.1-2013.3	1981.7-2020.3	1990.1-2020.3
$corr(\pi_t^{\text{exp}}, O_t)$	11.6%	33.9%	71.2%	4.6%	29.0%
$\hat{\beta}$	0.004	0.009	0.021	0.002	0.008
$\hat{t}_\beta$	1.08	2.24	5.39	0.39	1.80
R^2	1.3%	11.5%	50.7%	0.2%	8.4%

NOTES: Estimates based on regressions of $\pi_t^{\text{exp}} - \pi_t^{\text{exp},SPF}$, $\pi_t^{\text{exp},SPF}$ and π_t^{exp}, respectively, on an intercept and O_t for alternative estimation periods and data frequencies. $\hat{t}_\beta$ is based on Newey-West standard errors with a truncation lag of 8 for quarterly data and 24 for monthly data.

Appendix C: Approximating the Nonstandard Distribution of the t-Test Statistic under $H_0 : \beta = 0$

We approximate the null distribution of the t-test statistics in Table 1 based on a bivariate monthly data generating process (DGP) that treats realizations of inflation expectations and of the log price of oil (or, alternatively, the log price of gasoline) as mutually independent, ensuring that their correlation and hence β is zero.

It is well known that the null distribution of the t-statistic in regressions of an I(0) variable on a constant and an I(1) variable is nonstandard in general. This problem is particularly severe when the dependent variable is positively serially correlated (see Stewart 2011).

We model $o_t = \log(O_t)$ as I(1) such that Δo_t is I(0). As shown in Figure B1, Δo_t has s stable mean and unconditional variance, lending support to this assumption. In contrast, ΔO_t is not I(0), because its variance is not stable over time. Note that the variance dynamics in this series cannot be captured by a GARCH model, for example. Thus, $O_t = \exp(o_t)$ is a nonlinear transformation of an I(1) variable, which means that the null distribution of the t-statistic when regressing $\pi_t^{\exp}$ on O_t will differ from the null distribution when regressing $\pi_t^{\exp}$ on o_t.

Figure C1: Alternative representations of the WTI price of crude oil, 1978.1-2020.4
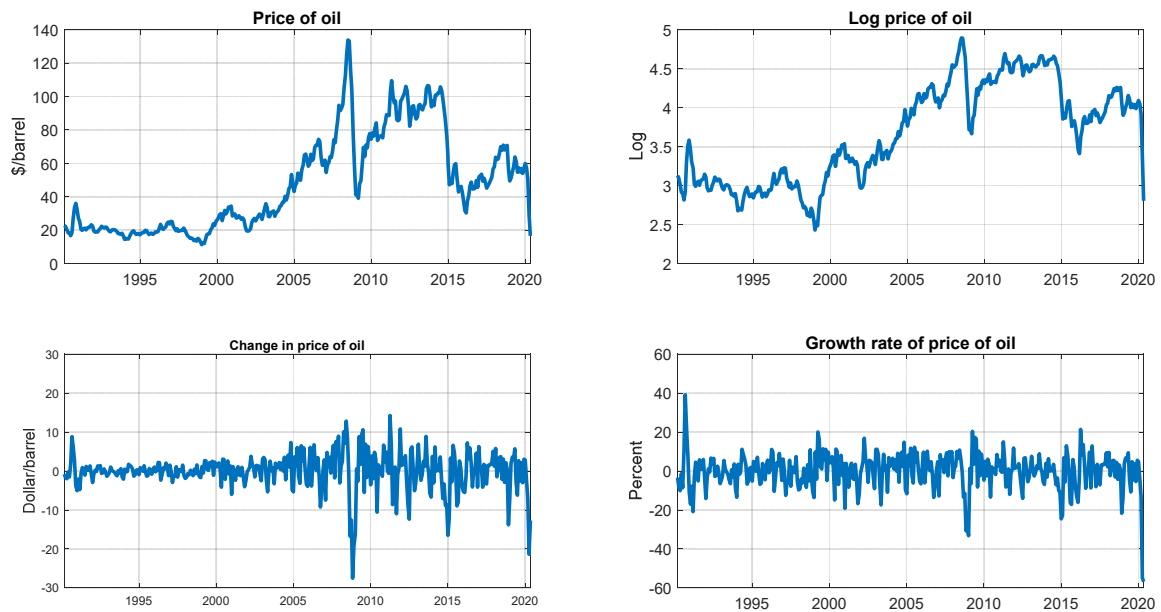
NOTES: The oil price is the spot price for WTI crude oil reported by the EIA.

As is common in the literature, we postulate that $\pi_t^{\exp}$ follows a stationary AR(1) process, $\pi_t^{\exp} = \alpha_0 + \alpha_1 \pi_{t-1}^{\exp} + \varepsilon_t^{\exp}$, where $\varepsilon_t^{\exp} \sim N(0, \sigma_{\exp}^2)$. Similar results would be obtained when allowing for longer lags. The parameters of this process may be recovered from the data. The estimated slope parameter is 0.84.

The log-level of the price of oil, o_t, is independently generated by cumulating realizations of $\Delta o_t = \mu_o + \sigma_o \varepsilon_t^o$, where ε_t^o is a Student-t_4 innovation (standardized to have mean zero and variance 1) and μ_o σ_o are calibrated to match the mean and the standard deviation of Δo_t in the data. In other words, $\varepsilon_t^{\exp}$ and ε_t^o are mutually independent. The assumption that o_t approximately follows a random walk is consistent with Figure C1 (see also Alquist, Kilian and Vigfusson 2013). The importance of modeling ε_t^o as a fat-tailed distribution is also illustrated in Figure C1. The same DGP may also be used to generate realizations of $O_t = \exp(o_t)$. Realizations of the price of gasoline may be generated analogously, by replacing the price of oil in the DGP by the price of gasoline and recalibrating the parameters.

This DGP allows us to simulate the finite-sample distribution of the t-statistic under $H_0 : \beta = 0$ in repeated sampling for the sample size of interest. We generate synthetic data from the estimated process of the same length as the actual data. For each random draw, we regress the simulated time series for $\pi_t^{\exp}$ on an intercept and the log-level (or the level) of the simulated oil (or gasoline) price, allowing us to build up the empirical distribution of the t-statistic. While there is no reason for this specific DGP to be the correct process under the null necessarily, the point of this exercise is to illustrate that the distribution of the t-statistic for $\hat{\beta}$ is far from the N(0,1) distribution under empirically plausible assumptions.

Figure C2 shows the finite-sample null distributions for the log-prices of oil and the log price of gasoline obtained based on 100,000 Monte Carlo trials from this DGP. Very similar results

Figure C2: Finite-sample null distributions for the t-test of $H_0 : \beta = 0$
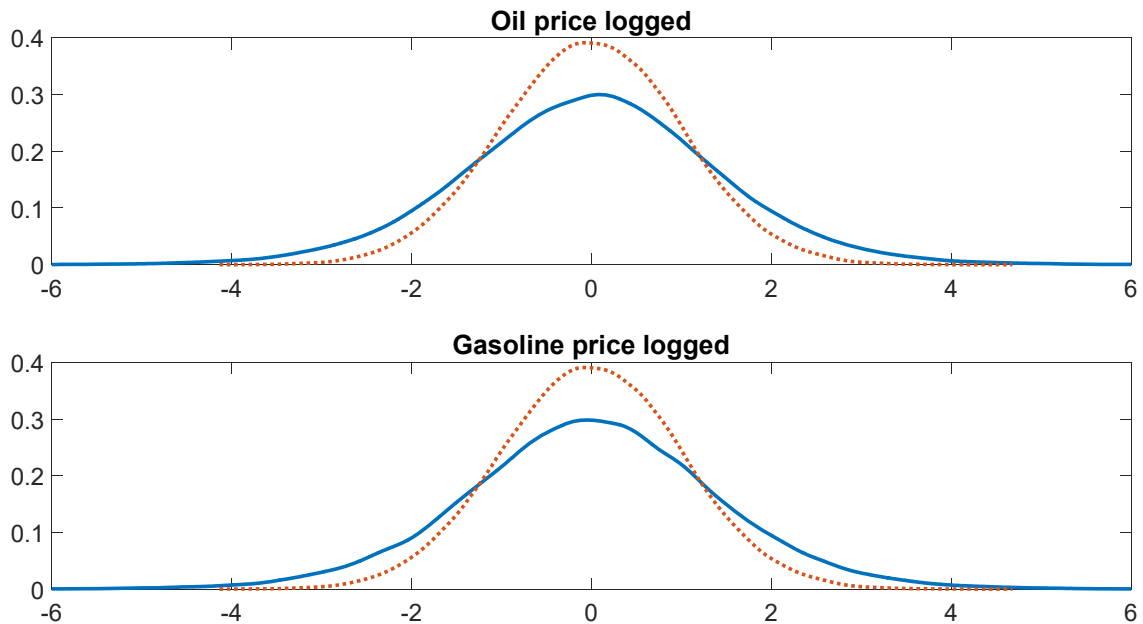
NOTES: All results based on NW(Andrews). Qualitatively similar results are obtained with fixed truncation lags. Based on 100,000 Monte Carlo trials from the DGP. The dotted lines show the N(0,1) distribution as a reference point..

hold for the level specification. Figure C2 illustrates that the null distribution is centered on zero, but has much fatter tails than the N(0,1) distribution.

Table 1 in the main text reports the finite-sample p-values. The corresponding finite-sample critical values for the one-sided t-test are shown in Table C1. The standard Gaussian critical values used in the literature are systematically too small, causing the test to reject too often.

Table C1: Finite-sample critical values based on equations (1) and ($1'$), 1990.1-2020.4

		50%	90%	95%
Oil price	Level	0.01	1.86	2.45
	Log-level	0.01	1.77	2.33
Gasoline price	Level	0.00	1.81	2.38
	Log-level	0.00	1.78	2.33
N(0,1) critical values		0	1.28	1.65

NOTES: All results based on 100,000 Monte Carlo trials. The t-statistics are based on Newey-West standard errors with the truncation lag selected as in Andrews (1991).

The problem of nonstandard critical values may be circumvented by regressing inflation expectations on $\Delta o_t \approx (O_t - O_{t-1}) / O_{t-1}$. Table C3 shows that in this case the statistical relationship becomes significant, but the R^2 becomes much smaller.

Table C3: Estimates of equation ($1'$) with Regressor Transformed to Growth Rate, 1990.1-2020.4

|	Growth rate of oil price	Growth rate of gasoline price
Correlation with $\pi_t^{\exp}$	14.3%	24.5%
R^2	2.0%	6.0%
$\hat{\beta}$	1.145	3.195
$t_{\hat{\beta}}$	2.246	3.787
p-value	0.012	0.000

NOTES: The standard errors underlying the t-statistics are computed based on Newey-West standard errors using the data-based estimator of the truncation lag proposed by Andrews (1991). The asymptotic distribution is standard.

Appendix D: The Unreliability of Correlation Estimates When One Variable Is I(1)
Table B1 shows that estimates of the correlation between inflation expectations and the price of oil are highly unstable over time. The point is reinforced by the evidence in Figure D1.

Figure D1: Rolling window estimates of the correlation between $\pi_t^{\exp}$ and O_t
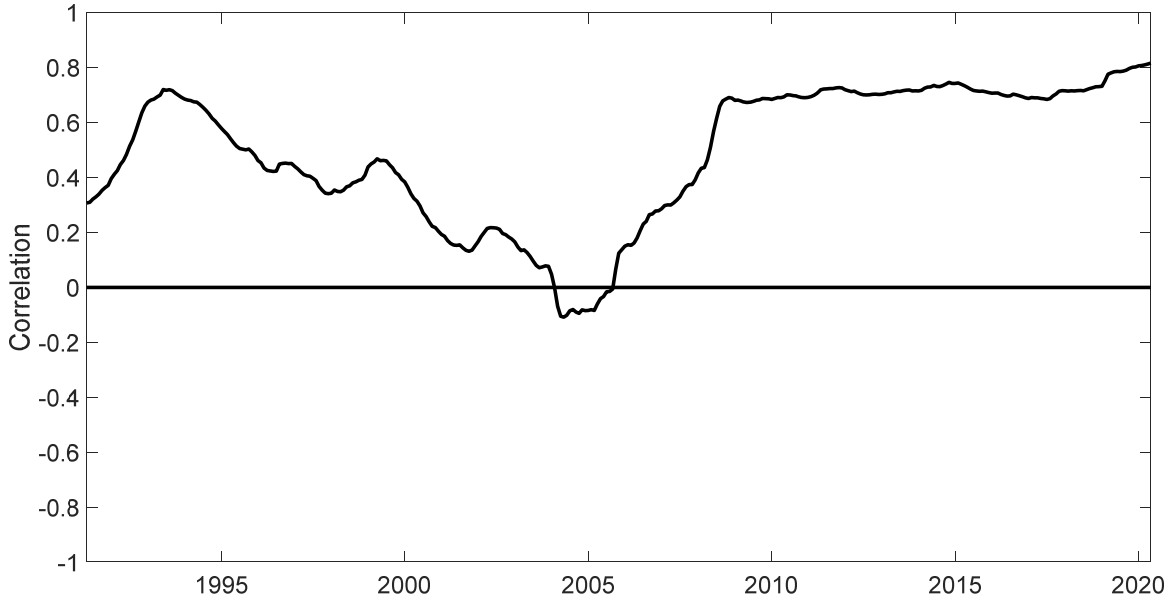
NOTES: The length of the rolling window is 159 monthly observations, corresponding to the length of the 2000.1-2013.3 estimation period.

The following simulation experiment supports the view expressed in Section 2 that the erratic behavior of the correlation (and by extension that of $\widehat{\beta}$ in the static regression) is driven by the fact that the oil price is not stationary. Consider the sample period 1990.1-2013.3. Suppose that $O_t = \exp(o_t)$, $t = 1,...,279$, where $\Delta o_t = \mu_o + \sigma_o \varepsilon_t^o$, μ_o and σ_o are calibrated to the WTI price data and $\varepsilon_t^o \sim NID(0,1)$, is generated independently of the observed $\pi_t^{\exp}$. Then, in repeated trials, the average absolute difference between the correlation of O_t with $\pi_t^{\exp}$ in the first half of the sample and the same correlation in the second half of the sample is 56 percentage points.

## Appendix E: The Prior Specification for the Structural VAR Model

The n-dimensional reduced-form VAR model is estimated based on a diffuse uniform-Gaussian inverse Wishart prior, as in Karlsson (2013). The prior of the VAR slope parameter vector is $\beta \sim N(\beta_0, \Sigma \otimes \Omega_0)$, where the prior mean β_0 is set to zero and Ω_0 is a diagonal matrix with j^{th} diagonal element $\left(\frac{1}{\sigma_j^2}\right)\left(\frac{0.2}{l}\right)^2$, σ_j^2 is approximated as the residual variance of an AR(1) regression for variable j, l indicates the lag, and $\Sigma \sim IW(S_0, \alpha_0)$ with

$$S_0 = (\alpha_0 - n - 1)\begin{pmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & \sigma_n^2 \end{pmatrix}$$

and $\alpha_0 = n + 2$. Using the approach of Inoue and Kilian (2020b), it can be shown that this prior is largely uninformative for the impulse responses in that the response functions that minimize the absolute loss function under the prior are almost invariably flat at zero, except when constrained by sign restrictions. In the rare cases, where these responses are not zero, the prior is not driving the posterior estimates shown in Figure F1. Thus, the differences between Figure E1 and Figure F1 are driven by the data.
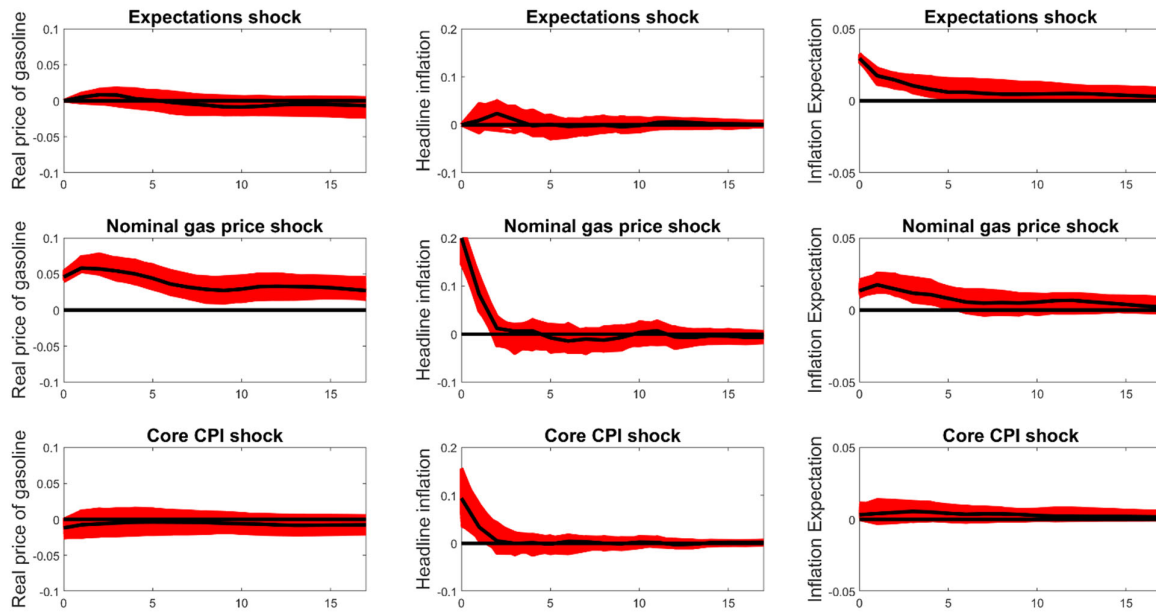
Figure E1: Impulse response estimates and 68% joint credible sets simulated from the prior distribution
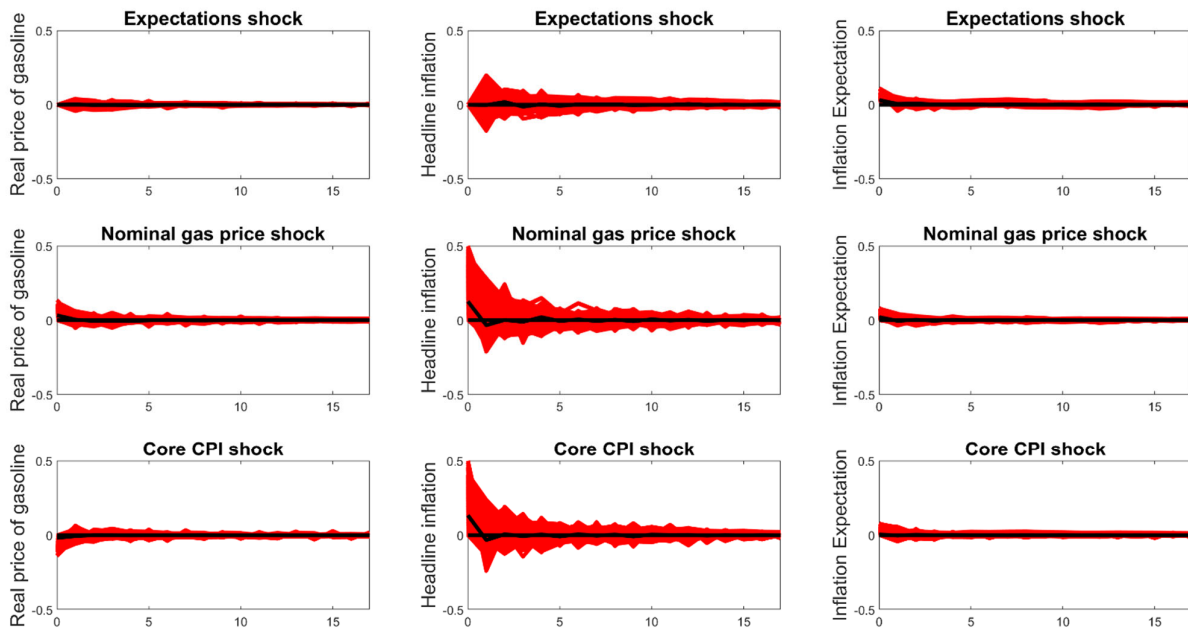
NOTES: The set of impulse responses shown in black is obtained by minimizing the absolute loss function in expectation over the set of admissible structural models, as discussed in Inoue and Kilian (2020a). The responses in the corresponding joint credible set are shown in a lighter shade.

Appendix F: Estimates of the Baseline Model

Figure F1: Impulse response estimates and 68% joint credible sets, 1981.7-2020.4

NOTES: The set of impulse responses shown in black is obtained by minimizing the absolute loss function in expectation over the set of admissible structural models, as discussed in Inoue and Kilian (2020a). The responses in the corresponding joint credible set are shown in a lighter shade.

### Figure F2: Historical decomposition of household inflation expectations, 1990.1-2020.4
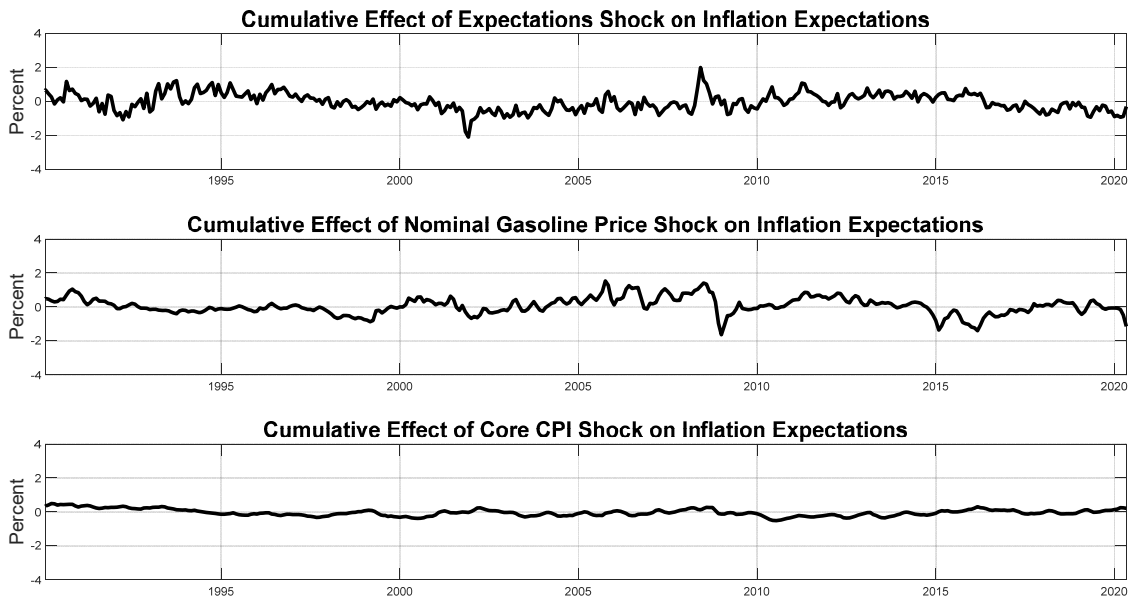
NOTES: The pre-1990 data have been discarded to reduce transient dynamics and to make the results compatible with the earlier regression evidence.

Appendix G. Additional Sensitivity Analysis

(a) Baseline model after dropping sign restrictions on inflation expectations

Figure G1: Impulse response estimates and 68% joint credible sets, 1981.7-2020.4.
Estimate after dropping sign restrictions on inflation expectation from baseline model
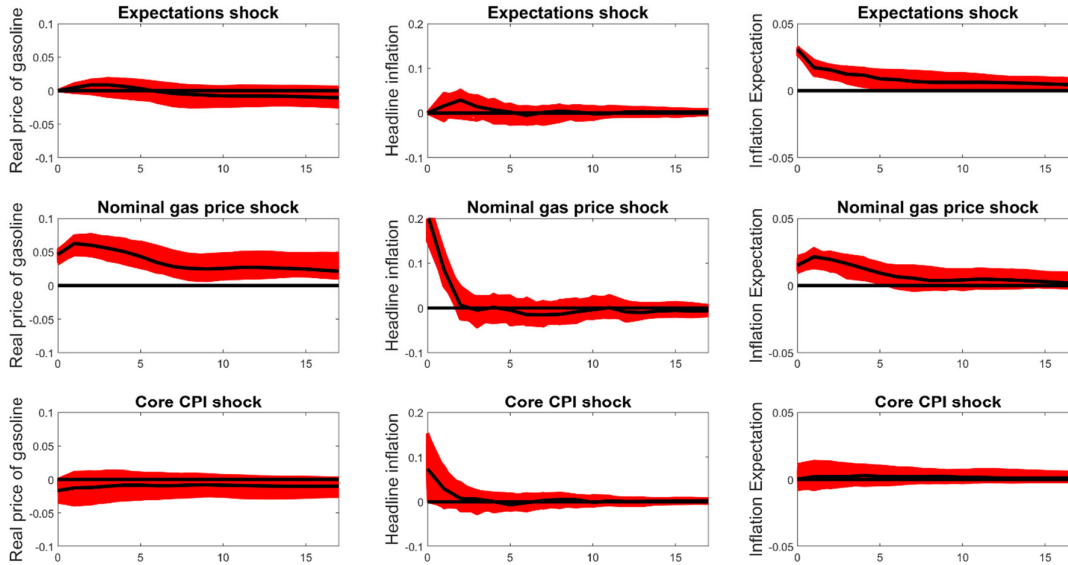
NOTES: See Figure F1.

(b) Alternative Partially Identified Model

Figure G2: Actual mean one-year inflation expectation in *Michigan Survey of Consumers* and counterfactual series in the absence of nominal gasoline price shocks, 1990.1-2020.4
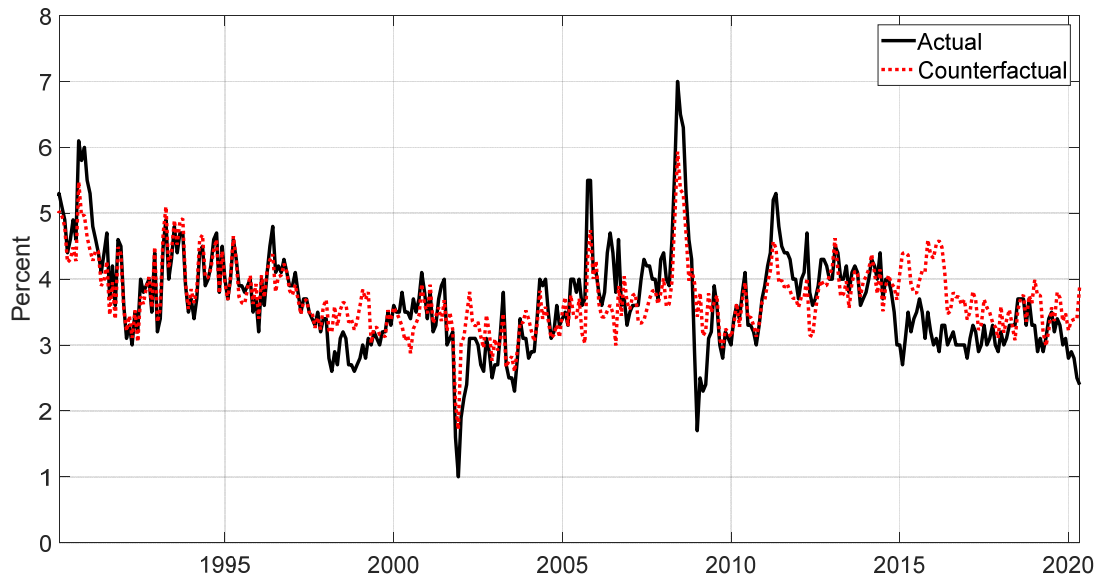

NOTES: The counterfactual time series is obtained by subtracting the cumulative effect of nominal gasoline prices shocks on household inflation expectations from the actual data after rescaling the fitted data to represent annualized inflation rates.

(c) Median Versus Mean Household Inflation Expectations

Our analysis so far has focused on the mean one-year household inflation expectations, as used by Coibion and Gorodnichenko (2015). One reason why they focus on the mean is that only the mean is available for the quarterly MSC data used in constructing the Phillips curve. The Michigan Survey of Consumers does not provide quarterly median household inflation expectations. Clearly, the median household inflation expectation is preferred by many analysts working with monthly inflation expectations data. Figure G3 shows estimates for the baseline model with median inflation expectations replacing the mean expectation. The estimates are very similar. For example, of the 1.5 percentage point cumulative increase in inflation expectations during 2009.1-2013.3, as before, 1.4 percentage points are explained by the cumulative effect of nominal gasoline price shocks. The response estimates are also similar to the baseline model.

Figure G3: Impulse response estimates and 68% joint credible sets, 1981.7-2020.4.
Alternative baseline model estimate based on median household inflation expectation
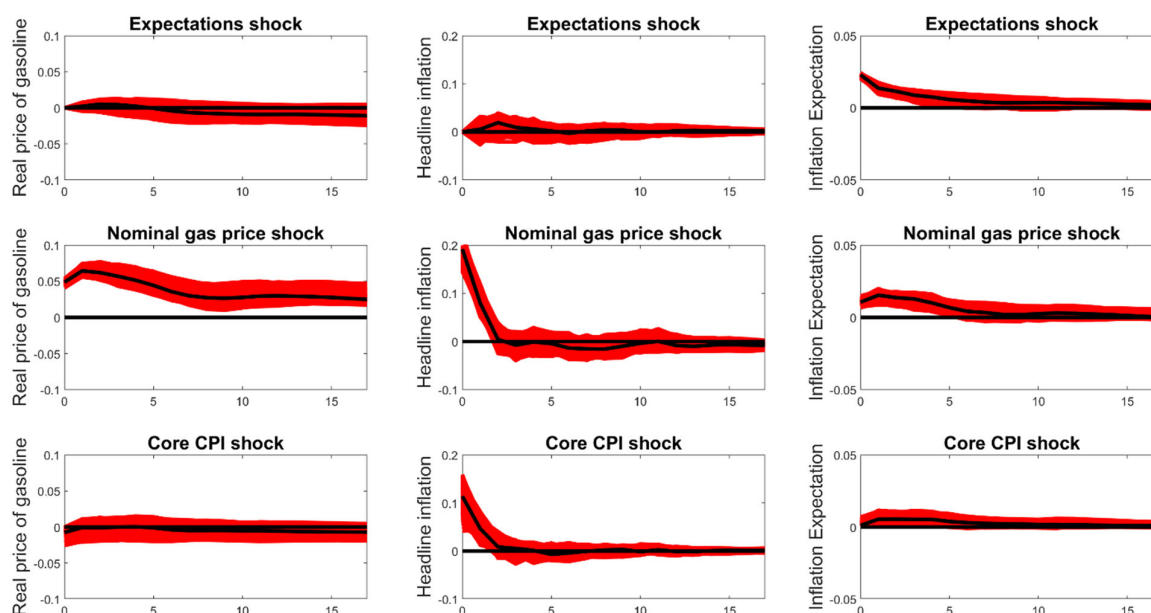
NOTES: See Figure 2.

(d) Temporal Stability of the Structural Model

One of the drawbacks of the reduced-form evidence discussed in Section 2 is the temporal instability of the correlation and slope estimators which arises from the fact that we regressed an I(0) variable on an I(1) variable (or a nonlinearly transformed I(1) variable). This problem does not extend to the reduced-form correlations between the variables included in the baseline or the alternative VAR model because the latter variables have been suitably transformed.

Instability in the reduced-form correlations of the VAR variables, however, may arise because the composition of the structural shocks in the VAR model evolves over time. For the period starting in 1990.1, the unconditional correlation between inflation expectations and

the log real price of gasoline is 0.182.[19] When conditioning on the variation induced by nominal gasoline price shocks, this correlation rises to 0.607, indicating a much tighter relationship. When conditioning on the other two structural shocks combined, the correlation drops to -0.216. Thus, changes in the relative importance of these shocks over time, as indicated by historical decompositions, will affect the reduced-form correlation obtained on subsets of the estimation period. This instability, however, need not be an indication of time variation in the structural model because it arises even when the underlying structural VAR model is temporally stable.

One may object that perhaps the relationship between gasoline price shocks and inflation expectations in the structural model has evolved over time and has become stronger in recent years. If there had been a structural change, one would have expected this change to have happened in the early 1990s, which is when the correlation evidence is getting stronger. One way of addressing this concern is by re-estimating the structural VAR model on data for 1990.1-2020.4. We find that the resulting impulse response estimates are virtually identical, indicating that the baseline structural VAR model is stable. The impact response of inflation expectations to a gasoline price shock that raises the nominal price of gasoline by 10% is only slightly higher with 0.4 percentage points at annualized rates, suggesting that there has been no important structural change in this relationship since the 1980s.

(d) Extended Structural VAR Model with a Measure of Economic Slack

Our baseline structural VAR model is a behavioral model of the formation of household inflation expectations. The objective of estimating this model is not to estimate the Phillips curve, but to understand the determinants of one of the variables in the expectations-augmented Phillips curve. Of course, if such a Phillips curve existed, the information set of the VAR model would change. We therefore also report results for a VAR model that, in addition, includes the monthly unemployment rate as a proxy for economic slack. Since extending the baseline model (2) to include the unemployment rate affects the interpretation of nominal gasoline price shocks, as discussed in Section 3, we work with the alternative partially identified structural VAR model. Because that model is block recursive, the responses are invariant to the identification of the remainder of the structural VAR model.

Figure G4 shows that the impulse response estimates are largely unchanged relative to the baseline model. The impact response of inflation expectations to a 10% nominal gasoline price shock is 0.4 percentage points at annualized rates, and 33% of the variation in household expectations are explained by this shock, close to the baseline model. The counterfactual is generally similar, but suggests a somewhat lower cumulative contribution of 0.8 percentage points of nominal gasoline price shocks to the cumulative increase of 1.5 percentage points in inflation expectations during 2009.1-2013.3.

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[19] This compares to 0.146 in Table 2 for the log nominal gasoline price.

Figure G4: Impulse response estimates and 68% joint credible sets, 1981.7-2020.4.
Partially identified model extended to include the unemployment rate.
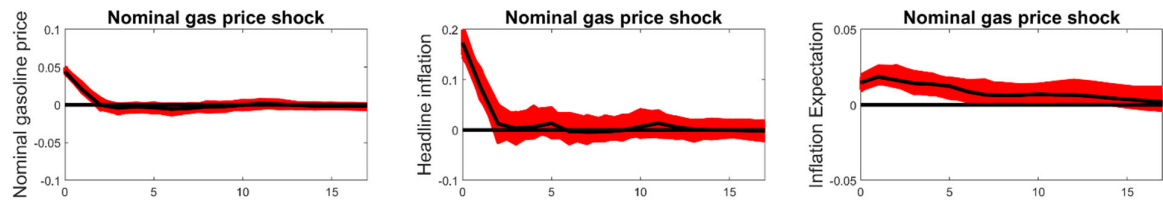
NOTES: See Figure 1.

Appendix H: Partial identification in sign-identified models

An interesting question is whether we could have estimated the baseline model of Section 3 based only on the sign restrictions on the impact responses to the nominal gasoline price shock, dispensing with all other identifying restrictions. The short answer is that we could have, but that this exercise would not have been econometrically meaningful.

As is well known, estimating partially identified models is straightforward when the structural impact multiplier matrix is block recursive, as in the alternative model of Section 3.4.2, because the responses of interest are invariant to the identification of the rest of the model. This invariance result does not hold in sign-identified structural VAR models.

Intuitively this happens because in sign-identified structural VAR models seemingly unrelated sign restrictions in the remainder of the structural VAR model reduce the set of admissible responses we are primarily interested in and hence help sharpen inference. A different way of putting this is to say that estimating partially identified structural VAR models based on sign restrictions for one shock only tends to be uninformative.

This point is well understood in the VAR literature. It can be traced to Canova and Paustian (2011) who first showed that imposing only a few sign restrictions in general is not enough to recover precise and economically meaningful SVAR response estimates. Canova and Paustian concluded that we need to use all restrictions available to the researcher, requiring more attention to the economic underpinnings of the identifying assumptions and arguing for fully identified models. Kilian and Murphy (2012) took this point a step further and showed that not imposing all of the relevant identifying restrictions may severely distort posterior inference. Thus, imposing the extra restrictions is not an option, but a requirement.

It thus should not come as a surprise that when only retaining the sign restrictions identifying the nominal gasoline price shock, the Bayes response estimates still look qualitatively similar, but are very imprecisely estimated (see Figure H1). The impact response of a 10% nominal gasoline price shock on inflation expectations is 0.7 percentage points at annualized rates (much higher than in the baseline model) and the lower and upper bounds are 0 and 16.3. This result illustrates that the other identifying restrictions are required for reliable inference in the baseline model, but, as discussed in Section 3.4.2, there is an alternative block recursive model that allows us to assess the validity of the baseline model.

Figure H1: Impulse response estimates and 68% joint credible sets, 1981.7-2020.4. Model estimate after dropping all restrictions in the baseline model but those for the nominal gasoline price shock.
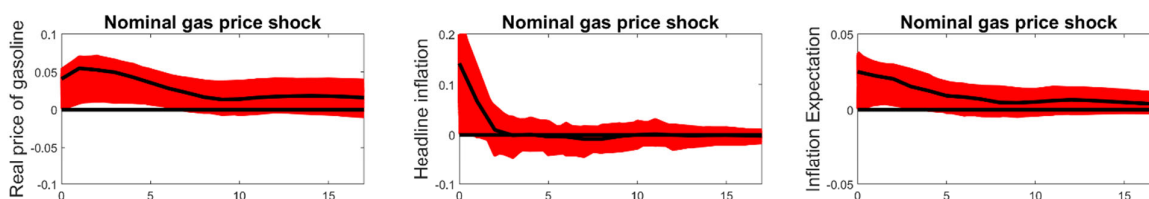
NOTES: See Figure 1. Unlike in the baseline model, no importance sampler is needed because of the absence of zero restrictions.