Staff Working Paper/Document de travail du personnel—2022-52

Last updated: December 20, 2022

Are Temporary Oil Supply Shocks Real?

by Johan Brannlund,[1] Geoffrey Dunbar[2] and Reinhard Ellwanger[2]

[1] Corporate Services
[2] International Economic Analysis Department
Bank of Canada
gdunbar@bankofcanada.ca

DOI: https://doi.org/10.34989/swp-2022-52 | **ISSN** 1701-9397

Acknowledgements

We thank Ron Alquist, Thomas Lee, Rob Vigfusson, Lutz Kilian and seminar participants at the Bank of Canada and the JPMCC Research Symposium for helpful comments. The views expressed in this paper are those of the authors and no responsibility for them should be attributed to the Bank of Canada.

Abstract

Hurricanes disrupt oil production in the Gulf of Mexico because producers shut in oil platforms to safeguard lives and prevent damage. We examine the effects of these temporary oil supply shocks on real economic activity in the United States. We find no evidence that temporary oil supply shocks affect state-level employment or indirectly affect industrial production in sectors not immediately related to oil production. We find that the temporary oil supply shocks have local, temporary price effects—mainly on gasoline prices—and that broader consumer price index inflation is also temporarily affected. In addition, we find no effect on imports, exports, exchange rates or the import price of oil. Our results suggest that oil reserves held by US refineries are largely sufficient to absorb any temporary disruptions to production.

Topics: Business fluctuations and cycles; Inflation and prices
JEL codes: E31, E32, Q31, Q41, Q43

Résumé

Les ouragans perturbent la production de pétrole dans le golfe du Mexique, car les producteurs ferment les plateformes pétrolières pour protéger des vies et éviter les dommages. Nous examinons les effets de ces chocs temporaires d'approvisionnement en pétrole sur l'activité économique réelle aux États-Unis. D'après notre étude, rien n'indique que ces chocs influent sur l'emploi au niveau des États ou se répercutent indirectement sur la production industrielle de secteurs qui ne sont pas étroitement liés à la production pétrolière. Nous constatons qu'ils ont des effets locaux et passagers sur les prix – principalement ceux de l'essence – ainsi qu'une incidence temporaire sur l'inflation mesurée par l'indice des prix à la consommation global. De plus, nous n'observons aucun effet sur les importations, les exportations, les taux de change ou les prix à l'importation du pétrole. Nos résultats donnent à penser que les réserves de pétrole détenues par les raffineries américaines sont largement suffisantes pour absorber toute perturbation temporaire de la production.

Sujets : Cycles et fluctuations économiques; Inflation et prix
Codes JEL : E31, E32, Q31, Q41, Q43

1 Introduction

Conventional wisdom suggests that oil supply shocks affect economic activity because of the widespread use of oil in transportation and manufacturing. Episodes such as the stagflation in the US during the 1970s, which coincided with the creation of the Organization of the Petroleum Exporting Countries (OPEC), and the shale oil boom in Texas and the US Midwest during the 2010s support this narrative. However, differentiating between contemporaneous correlation and causation of oil production and economic activity is difficult because exogenous variation for the former is typically hard to find. In this paper, we investigate the effect of temporary oil supply shocks on US economic activity using exogenous variation in US oil supply that results from hurricane activity in the Gulf of Mexico. We find no evidence that temporary oil supply shocks have real effects on US economic activity.

Hurricanes disrupt oil production on offshore platforms in the Gulf because they are potentially both deadly and extremely costly in terms of physical damage to oil rigs and the environment. Oil rigs that are within the forecast path of a hurricane shut in production when hurricanes in the Gulf are imminent.[1] We use detailed monthly production data from the Bureau of Ocean Energy Management (BOEM) to create a time series of oil production for leases granted to producers that are located on the Gulf of Mexico Outer Continental Shelf (OCS). Then, similar to Brannlund, Dunbar, Ellwanger, and Krutkiewicz (2022), we construct an indicator of hurricane activity in the Gulf and interact this indicator with the monthly change in oil production in the Gulf to measure production changes that result from rigs shutting in production in advance of anticipated hurricanes. Underlying our identification is an assumption that, at least in the short run, economic activity does not cause hurricanes in the Gulf. Consequently, production changes in advance of and during the hurricane are exogenous shocks.[2]

We investigate how hurricane-induced production changes affect different measures of (disaggregated) US economic activity: the real and nominal imported prices of oil reported by the US Energy Information Administration (EIA); city-level gasoline prices for 8 US cities; state-level employment for 44 US states; total and sub-indices of US industrial production; total and sub-indices of Consumer Price Index (CPI) inflation; and Canadian energy exports and the US/CAD exchange rate. For the spatially disaggregated data on gasoline prices and state-level employment, we select only cities and states that do not border the Gulf and are unlikely to have been directly affected by the hurricanes. We do not have access to spatially

[1]"Shut in production" refers to the temporary cessation of oil production and the removal of personnel from rigs. Typically, well heads are also secured to prevent leakage and environmental damage. The US Bureau of Safety and Environmental Enforcement (BSEE) publishes daily updates on the percentage of platforms that shut in production. See, for example, this press release for Hurricane Ida in 2021: `https://www.bsee.gov/newsroom/latest-news/statements-and-releases/press-releases/bsee-monitors-gulf-of-mexico-oil-and-48`.

[2]In contrast, production losses from hurricane *damages* are not exogenous sources of identifying information for production disruptions because the timing of the assessments and repairs (and even the decision to repair at all) likely depends on economic conditions such as oil prices. It is also the case that hurricanes disrupt shipping, so refiners in the Gulf are not able to replace lower local production with oil imported by tankers during the period of the hurricane (Dunbar, Steingress, and Tomlin, 2022).

disaggregated industrial production data, so we instead trace out how oil supply shocks affect different aspects of production. Finally, we focus on energy exports from Canada because it is already a large energy exporter to the US with pipeline access to US refineries. Thus, it would seem plausible that a demand response for oil to replace lost production in the Gulf might affect energy exports from Canada.

To determine the impact of oil supply shocks, we follow Jordá (2005) and Montiel Olea and Plagborg-Møller (2021) and estimate local-projection regressions.[3] Using local projections instead of VARs is advantageous in our setting: local projections are easily adaptable to different target variables, and we can estimate spillovers across regions and sub-indices without imposing structural assumptions. Overall, we find little statistically significant evidence that temporary oil supply shocks affect any broad measure of US economic activity. We do find that temporary oil supply shocks affect contemporaneous industrial production indices that directly measure oil production. We also find that temporary oil supply shocks affect gasoline prices in our sample of US cities one month after the hurricane and that these increases also affect CPI inflation. However, there is no evidence that temporary oil supply shocks affect employment, imported oil prices, other sub-indices of industrial production or CPI inflation, Canadian energy exports or the CAD/US exchange rate. Our results suggest that temporary oil supply shocks are localized to the oil industry and do not broadly or indirectly affect US economic activity.

Our results pertain to temporary supply shocks and do not imply that persistent shocks, including unanticipated oil discoveries, are neutral for economic activity. The oil supply shocks identified in this paper also differ from news shocks about oil markets, such as those studied in Känzig (2021). Indeed, one contribution of our paper is to highlight differences between temporary oil supply shocks and information that changes the expected present value of future oil supply. As we document, the former have only modest transitory effects on gasoline prices whereas Känzig (2021) shows the latter affects real activity. These contrasting effects are easily rationalized if the temporary shocks we identify are at least partly insurable. We provide evidence that the oil supply shocks we identify are typically accompanied by drawdowns of crude oil inventories of similar magnitude. This response is consistent with the role of inventories for smoothing production disruptions highlighted in the theory of storage (Working, 1949 and Pindyck, 1994).

Our paper contributes to the literature on the effects of oil shocks on economic activity. One common approach in this literature is to identify oil supply shocks empirically using oil price data. Identification of supply (or demand) shocks using prices, absent exogenous variation, requires restrictions on supply and demand elasticities (see, e.g., Kilian and Zhou, 2020b). The use of structural models, primarily structural vector autoregressions (SVARs), to estimate the effects of oil supply shocks for economic activity is largely due to Kilian (2009). Kilian (2009) and Kilian and Murphy (2014) argue, using a SVAR that disentangles

[3] Recently, Plagborg-Møller and Wolf (2021) have demonstrated that local projections and vector autoregressions (VARs) estimate the same object, at least in the population, so our results should not be sensitive to our methodological choice to use local projections.

supply and demand shocks, that demand shocks were the main drivers of oil price changes. However, Baumeister and Hamilton (2019) and Caldara, Cavallo, and Iacoviello (2019) argue that structural VARs impose cross-equation restrictions on the estimates of supply and demand elasticities, which can affect, in turn, the interpretation of the importance of each shock. Baumeister and Hamilton (2019) show that relaxing identifying assumptions about the short-run response of oil supply to price changes implies a greater role for oil supply shocks. Similarly, Caldara, Cavallo, and Iacoviello (2019) use a narrative approach to estimate supply and demand elasticities that implies that oil supply shocks are the main drivers of oil price movements. Herrera and Rangaraju (2020) examine a suite of recent structural VAR models proposed in the literature and show that the estimated differences for the importance of oil supply shocks across the models depend largely on the Bayesian prior for the short-run supply elasticity and/or model specification. They argue that conditioning on a short-run supply elasticity that is close to microeconometric estimates in Anderson, Kellogg, and Salant (2018), Newell and Prest (2017) or Bjørnland, Nordvik, and Rohrer (2021), leads to similar conclusions across models that are largely consistent with Kilian (2009).

One lesson from our paper for this literature is that temporary supply shocks may not be identified using VAR-based decomposition strategies based on oil prices because crude oil prices do not respond to these shocks. The identification challenge is stark and basic: if temporary oil supply shocks do not affect crude oil prices, then crude oil prices cannot identify temporary oil supply shocks. The shocks we identify are, however, still oil supply shocks, and we find that they do affect some nominal series such as gasoline prices and the CPI and some real indices such as industrial production.[4] An implication of our study is that the effects of temporary supply shocks are likely to be reflected in the implied counterfactuals for VAR-based decompositions, which suggests that the estimated coefficients for the effects of oil shocks should be interpreted with caution in these settings.[5]

2 Empirical approach

Oil production in the Gulf shuts down in advance of hurricanes because of the anticipated risks to personnel, the environment and structures posed by the high winds and dangerous sea-state conditions that are caused by these violent storms.[6] To estimate the magnitude of these effects, we use lease-level data on oil rig locations

[4]The fact that we do not find a significant effect on crude oil prices might raise the question of why gasoline prices are affected at all by these shocks. One plausible explanation is that inventory management induces additional costs, which are passed on to retail prices.

[5]The direction of bias is, however, difficult to determine as the recent event study literature has shown. See, for example, de Chaisemartin and D'Haultfœuille (2020).

[6]That this occurs is well known, and the BSEE reports some production shut-in data in advance of known storms; see `https://www.bsee.gov/resources-tools/planning-preparedness/hurricane/activity-statistics-update`. Unfortunately, these data have several limitations, making it unsuitable for our analysis. First, the production shut-in reports provide only estimates of the number of barrels of oil not produced and not any possible production increases by unaffected rigs, and thus does not provide a measure of the overall supply effect. Also, the production shut-in data historically were typically reported only on weekdays, at least until the mid 2000s, which implies uncertainty over production losses on weekends. Finally, the

in the Gulf of Mexico, production data for the OCS from the US Bureau of Ocean and Energy Management (BOEM) and hurricane track data from the National Oceanic and Atmospheric Administration's (NOAA) National Center for Environmental Information; see Knapp, Kruk, Levinson, Diamond, and Neumann (2010) and Knapp, Diamond, Kossin, Kruk, and Schreck (2018).[7] Similar to Brannlund, Dunbar, Ellwanger, and Krutkiewicz (2022), we use the NOAA hurricane data to construct a hurricane indicator equal to 1 if a hurricane of any category greater than or equal to 1 on the Saffir-Simpson scale passes within 500km of a structure for any oil-producing lease in our sample in the Gulf of Mexico for which we have location data.[8] For our sample period of January 1980 to December 2019, our indicator equals 1 for a total of 43 months, which is roughly 9 percent of our sample. We interact this indicator with the monthly change in total offshore oil production calculated from the lease-level production data for each lease reported in the full BOEM data. The BOEM production data are based on monthly reporting for the lease holders for the purposes of royalty payments and cover the universe of oil leases administered by the BOEM in the OCS. We scale our interacted indicator by the EIA's total production for the US, lagged one month, so that our measure of the oil supply shock is easier to interpret. Our measure of the oil supply shock at time t is, therefore:

$$\Psi_t = \frac{\mathsf{I}_t(hurricane <= 500km) \times \Delta\mathsf{OCS}_t}{\mathsf{TotalUSOilProduction}_{t-1}} \times 100, \tag{1}$$

where $\mathsf{I}_t(hurricane <= 500km)$ is our hurricane indicator for period t, $\Delta\mathsf{OCS}_t$ is the change in the monthly oil production (in barrels) for the OCS administered by the US BOEM and $\mathsf{TotalUSOilProduction}_{t-1}$ is the total oil production of the US (in barrels) at time $t-1$. We scale the shock by 100 so that Ψ_t is measured in percentage points.

Figure 1 (a) plots the time series of our oil supply shock measure. The largest decline in production, roughly 20 percent of total US production, occurred in September 2008 during hurricanes Gustav and Ike, although the decline during Hurricane Katrina in 2005 was of a similar magnitude. Interestingly, there are also periods during which our oil supply shock measures are positive. These episodes appear to reflect production increases by producers far from the hurricane eye (though still within the 500km distance) during relatively less powerful hurricanes, or production increases after relatively milder hurricanes that passed quickly through the producing areas of the Gulf. One explanation is that these producers increase production in anticipation of other producers' production decreases that do not fully materialize.[9] These oil

BSEE reports production shut-in data only for storms that it deems to have had a significant impact on production and does not appear to define its threshold of significance.

[7]The BOEM data were obtained from `https://www.data.boem.gov/Main/Platform.aspx` and `https://www.data.boem.gov/Main/RawData.aspx`.

[8]The choice of 500km is arbitrary and reflects two considerations. First, the largest hurricanes can have diameters of roughly 300km; second, hurricane paths are uncertain and this uncertainty grows over projected distances. 500km appears a reasonable balance between these considerations; however, our results do not change significantly if we reduce this distance to 250km.

[9]There appear to be two plausible scenarios that explain why production may increase. (1) Producers overestimate the damage to their competitors, or (2) producers overestimate how long their competitors will take to restart production. Either case can rationalize the modest supply increases we observe in our data.

supply increases are still shocks in the sense that the additional production is in response to the hurricanes. Figure 1 (b) plots the distribution of affected leases in our sample. Higher values represent storms that affected a greater proportion of rigs in our data. Almost 100 percent of oil leases are within 500km of the modal hurricane. Hurricane Ingrid in 2013 affected the least proportion of leases (approximately 60 percent, by our measure). Hurricane Ingrid is also an example of a production increase which did not generate a production shut-in report from the BSEE but nevertheless led to a change in oil supply.

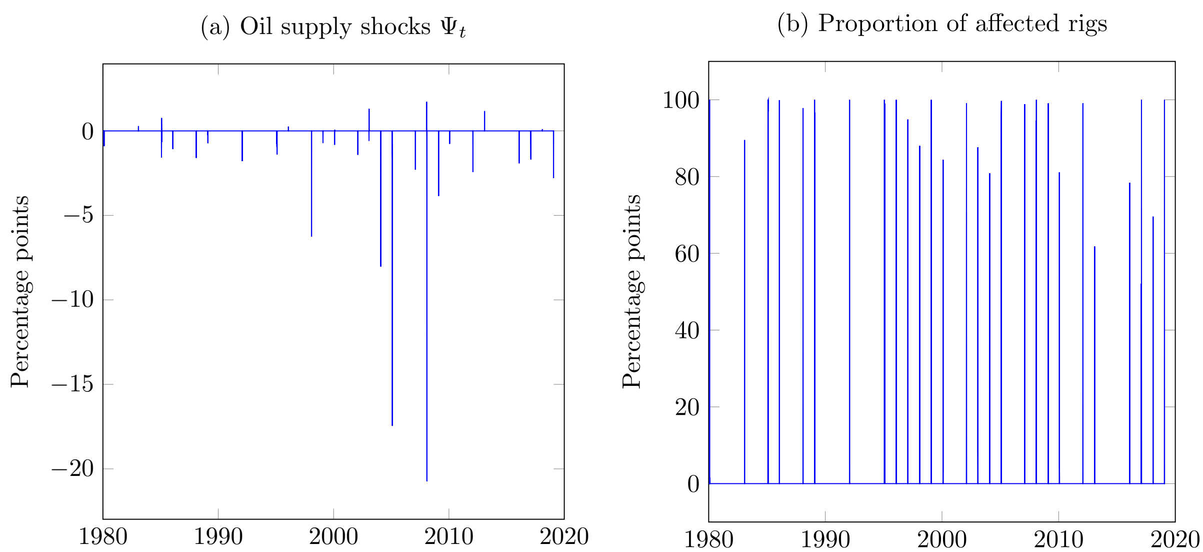
One might be concerned that our shock measure does not accurately capture unanticipated oil supply disruptions. There are two possible issues of concern. First, it is possible that our measure misses some hurricanes that disrupt production. Unfortunately, the US BOEM data do not include platform location data for roughly 1/3 of the sample of oil-producing leases, so we cannot directly measure hurricane disruption at the lease level (the BOEM data do include oil production for all leases, however). The subsample of known lease locations do, however, cover the common production areas of the Gulf, including deeper-water oil-producing areas such Green Canyon and Mississipi Canyon and the Garden Banks. Because we use the total oil production recorded by the BOEM to construct our oil supply shock, we can miss a supply disturbance only if a hurricane passes within 500km of an actual oil-producing rig that is not in our location data subset and this hurricane is at least 500km from a location that is in our data. Such an outcome appears very unlikely, since our location data cover most of the known oil-producing regions in the Gulf and the 500km radius from the known lease locations covers virtually the entire OCS region administered by the US.

The second concern is that we attribute oil supply disruptions to hurricane activity when other factors may also be responsible for the oil supply disturbance. This would suggest that we may overestimate the effect of the oil supply disturbance caused by the hurricane, since we attribute the entire disturbance to the hurricane shock. Any measurement error for our oil supply shock must be multiplicative because the modal value of the shock is zero (when there are no hurricanes). If measurement error was additive, it would imply an unrealistic restriction on the distribution of the error (it would also need to be zero precisely when no hurricanes were observed). Multiplicative measurement error implies $\Psi_t = \lambda_t \ddot{\Psi}_t$, where λ_t is measurement error and $\ddot{\Psi}_t$ is the true value of the oil supply shock (which is unobserved). It appears most plausible that we may over-attribute the production disruption to the hurricane, which implies $1 \geq \lambda_t > 0$ and, following arguments in Hwang (1986), our estimates of the effect of the oil supply shock may be biased upward.[10]

A final comment regarding the oil supply shock is that its sign is not normalized to represent supply shortfalls, as we consider both positive and negative shocks. Thus, for the regression specifications that we present in the subsections below, positive (negative) coefficient estimates imply an increase (decrease) in the dependent variable in response to higher oil production.

[10]Because we assume that hurricanes are (conditionally) random events, this measurement error is, however, uncorrelated with the production shock itself and does not imply correlation between the regression residuals and our shock series.

Figure 1: Hurricanes and oil supply shocks in the Gulf of Mexico



Notes: Oil supply shocks are expressed as a percentage of total US crude oil production. Monthly data, 1980-2019.

2.1 Oil supply shocks versus price shocks

We begin by examining the price responses to oil supply shocks for the US. Figure 1 (a) illustrates that the production losses from hurricane disruptions can be large as a proportion of total US oil production. The largest monthly fall in production–almost 17 million barrels of oil–occurred in 2008 because of hurricanes Gustav and Ike. This accounted for almost 20 percent of the prior month's total US oil production. It is plausible that these production losses increased US demand for imported oil, which should, in theory, have increased imported oil prices. Increased import demand would seem perhaps even more plausible since Brannlund, Dunbar, Ellwanger, and Krutkiewicz (2022) find that production losses for leases that are directly impacted by hurricanes can be persistent.

We first consider whether the oil supply disruptions are reflected in the imported crude oil prices reported by the EIA for the US for the years 1980-2019.[11] We assess this conjecture using the local projections method of Jordá (2005). Recently, Plagborg-Møller and Wolf (2021) have demonstrated that local projections and VARs estimate the same impulse response functions. Since we do not require structural methods to identify our supply shock, we choose to estimate the impulse responses using local projections. We follow Montiel Olea and Plagborg-Møller (2021) and include lags of the oil price to account for serial correlation. Our estimating equation for horizon h is:

[11] Imported oil prices were obtained from `www.eia.gov/oil_gas/petroleum/data_publications/petroleum_marketing_monthly/pmm.html` on August 10, 2021.

$$y_{t+h} = \sum_{i=1}^{k} \rho^{i,h} y_{t-i} + X_t \beta^h + \mu^h \psi_t + e_t \tag{2}$$

where y_{t+h} is the natural logarithm of the imported oil price (we consider both real and nominal); X_t is a vector of month and year dummy variables to account for residual seasonal and business cycle variation, and $\psi_t = ln(\Psi_t + \sqrt{1 + \Psi_t^2})$ is the inverse hyperbolic sine of Ψ_t. We transform Ψ_t using the inverse hyperbolic sine so that we can roughly interpret the coefficient estimates of μ^h as the price elasticities of oil supply shocks (see Bellemare and Wichman, 2020) and to reduce the influence of outliers.[12] Unlike logarithmic transformations, the inverse hyperbolic sine transformation is defined when $\Psi_t \leq 0$ as is the case in our data. We choose $h = \{0, 1, ...8\}$ and $k = 12$ for our estimation, but alternative choices of k greater than the maximum of h do not materially affect our results.[13] For both the real and nominal oil price series, our regressions have 468 observations, so we report Eicker-Huber-White standard errors as recommended by Montiel Olea and Plagborg-Møller (2021) rather than using a bootstrap method that might provide better finite sample performance. The results of Herbst and Johannsen (2020) suggest that any bias from serial correlation is unlikely to be severe for our application, given our numbers of observations.

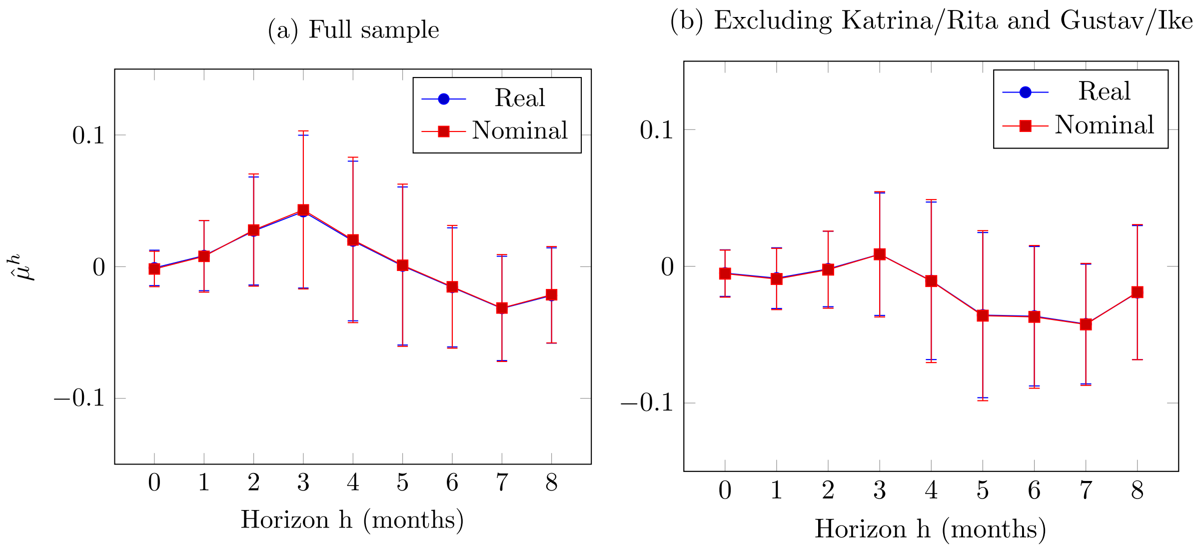
We present our results in Figure 2 (a). The impulse responses for both the real and nominal price series are effectively identical. The whisker bars report the symmetric 95 percent confidence intervals for the point estimates. None of the point estimates are significantly different from zero at any of the horizons up to eight months from the oil supply shock. In level terms, our estimates show that the peak elasticity response is at three months and is roughly 0.04 for both real and nominal oil prices. Generally, the modest response of crude oil prices to supply shocks is more compatible with evidence obtained from SVAR models that impose a lower short-run supply elasticity (Herrera and Rangaraju, 2020).

The shape of the impulse response that we plot in Figure 2 (a) is, itself, counter-intuitive because it suggests that import prices decrease several months after a negative oil supply shock, which is inconsistent with the textbook response to a negative supply shock that is uncorrelated with a demand shock. Crude oil prices are largely determined by refinery demand, and it is possible that our impulse responses for $h > 0$ confound damage to refineries or pipelines with the impact of the hurricane shut-in production shock. Kilian (2010) and Kilian and Zhou (2020a) argue that US refinery demand is an important factor in the determination of crude oil prices, particularly with respect to the impact of Hurricane Katrina on Gulf Coast refineries.

[12] The interpretation of μ^h is as the percent change in imported oil prices to a percent change in Ψ_t, as long as the shocks are sufficiently large such that $\sqrt{1 + \Psi_t^2} \approx \Psi_t$. Thus, a 100 percent increase in the shock would be equivalent to doubling Ψ_t and would imply a $2\mu^h$ change in imported oil prices.

[13] In general for all the results we present, alternative choices of k that are greater than the maximum of h do not materially affect our results. Our choices for h are largely data-driven in that we choose h such that any observed impulse response has largely reverted to zero by the maximum choice of h. We also generally set the maximum of h to be less than or equal to 8 months so that we do not confound a following year's hurricane season in our estimates.

Figure 2: Response of price of imported oil to oil supply shock ψ_t



Notes: ψ_t is the inverse hyperbolic sine transform of the percent oil supply shock Ψ_t. Whiskers indicate 95 percent confidence bands.

In our sample, there are two periods where hurricanes caused substantial disruption to refineries or pipelines: hurricanes Katrina and Rita in September 2005, and hurricanes Gustav and Ike in September 2008. To assess the impact of refinery or pipeline disruptions for the estimated impulse responses of imported crude prices, we re-estimate Equation (2) excluding those hurricanes from our sample period. Figure 2 (b) presents the estimated impulse responses. Figure 2 (b) suggests that the slope of the impulse response for $h \leq 4$ in Figure 2 (a) is largely influenced by hurricanes Katrina, Rita, Gustav and Ike. We find little evidence of any short-run impact from an oil supply shock on imported crude oil prices, even in level terms absent these hurricane episodes.

Our estimates suggest that there is no contemporaneous response of the price of imported oil to a transitory oil supply shock. This lack of response implies that identifying temporary oil supply shocks from oil prices is, at best, extremely difficult, at least for shocks localized to the US. For such shocks, even imposing a sign restriction on the short-run elasticity would seem to have little identifying power to differentiate the impulse responses at any horizon we consider. Another implication of the estimates is that there is little short-run change in US demand for imported oil in response to a temporary oil supply disruption.

2.2 Refineries and oil inventories

One reason that there might be no demand response for imported crude from transitory oil supply shocks is that refineries smooth such shocks using crude oil inventories. The stock of US crude inventories in October

2021 was, for example, equivalent to roughly 1 billion barrels of crude with approximately 40 percent held commercially (mainly by refineries) and 60 percent held in the strategic petroleum reserve (SPR). We next assess the impact of the oil supply shock for the oil inventories held by refineries and inventories held in the SPR. We use weekly data on oil inventories reported by the EIA that we convert to monthly frequency by taking the minimum reported stock in a given month.[14] We re-estimate our baseline local projection, Equation (2), using either the stock of crude reserves held by refineries or by the SPR as our dependent variable and replacing ψ_t by

$$\tilde{\Psi}_t = \mathsf{I}_t(hurricane <= 500km) \times \Delta\mathsf{OCS}_t.$$

$\tilde{\Psi}_t$ is simply the level shock in Gulf production. We note that the recent monthly production of crude oil in the Gulf is around 30 million barrels, so the inventory reserves are an order of 30 times larger.

Figure 3 (a) presents the estimated impulse responses for total US refinery inventories and SPR inventories. The estimated coefficient on $\tilde{\Psi}_t$, $\hat{\mu}$, can be interpreted as the portion of the oil supply shock smoothed by releases from inventories. There is a statistically significant drawdown of oil inventories in response to an oil supply shock both contemporaneously and one month after the shock. The point estimates are approximately 0.6 and 0.5, respectively, which suggests that the cumulative response is roughly identical to the level of the shock. There is some evidence that inventories are restocked five to seven months after the shock; however, these point estimates are not statistically different from zero at a 5 percent level of significance. There is evidence of a contemporaneous response of inventories held in the SPR, with the impulse response point estimates being significantly different from zero at a 5 percent level of significance until $h = 7$. However, the point estimates are relatively smaller, with the maximum point estimate roughly half of the contemporaneous response of commercial crude oil inventories.

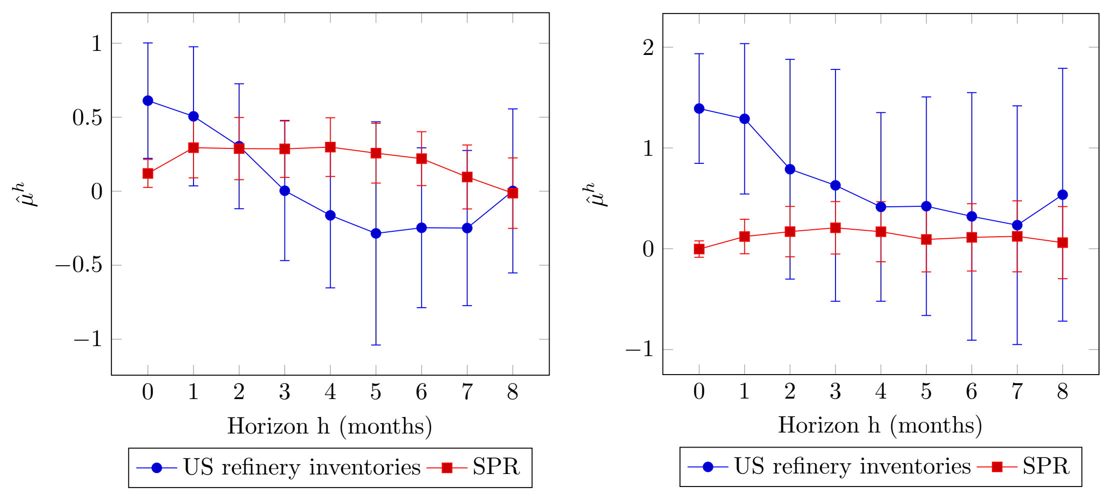
Figure 3 (b) presents the estimated impulse responses for US refinery inventories and SPR inventories excluding hurricanes Katrina, Rita, Gustav and Ike. Somewhat interestingly, the inventory drawdowns by US refiners appear to be larger than the actual production losses incurred as a result of the oil supply shock on impact and also one month after the shock. However, there is little evidence of a long-term effect as the remaining point estimates are not significantly different from zero at the 5 percent level of significance. In terms of SPR inventory responses, none of the point estimates are significantly different from zero. These estimates are generally consistent with a rather sporadic use of the SPR in the aftermath of selected hurricanes.[15]

[14] The data were obtained from `https://www.eia.gov/dnav/pet/pet_stoc_wstk_dcu_nus_w.htm` on November 12, 2021.

[15] SPR releases under exchange agreements occurred after Hurricane Lili in 2002, after Hurricane Ivan in 2004, after Hurricane Isaac in 2012 and after Hurricane Harvey in 2017, see `https://www.energy.gov/fecm/strategic-petroleum-reserve-0`.

Figure 3: Response of crude oil inventories to oil supply shock $\tilde{\Psi}_t$

(a) Full sample　　(b) Excluding Katrina/Rita and Gustav/Ike



Notes: Estimated effect on log inventories. $\tilde{\Psi}_t$ is the total oil supply shock in percent of previous month production. $\hat{\mu}^h$ represents the change in inventories relative to the size of the supply shock. Whiskers indicate 95 percent confidence bands.

2.3 City gasoline prices

The impulse response estimates presented in section 2.1 suggest that the oil supply shocks Ψ_t lower the quantity of oil in the US economy, but that inventory drawdowns likely mitigate the supply shock. Thus, goods (or services) that use oil as an input may experience only a muted supply shock to their production. Roughly 40 percent of US oil production is refined into gasoline, so a quantity shock in US crude oil should impact gasoline production.

We obtain monthly gasoline prices for 10 large US metropolitan areas from the EIA: Boston, Chicago, Cleveland, Denver, Houston, Los Angeles, Miami, New York City, San Francisco and Seattle.[16] The gasoline price data are monthly, starting in June 2000 for all cities except Boston, Cleveland, Miami and Seattle, which start in June 2003. We follow the same specification as Equation (2) and estimate local projections for each city in our sample individually. We set $k = 6$ and consider $h = \{0, 1, 2, 3\}$ and again report Eicker-Huber-White standard errors because our sample lengths are near the upper bound of the sample lengths discussed in Herbst and Johannsen (2020) as potentially being biased by serial correlation. We continue to include month and year dummy variables to account for seasonal and trend changes in gasoline prices. Hurricanes in our sample occur only between June and November and the monthly dummy variables account for this seasonal variation.

[16] Data were downloaded from: `http://www.eia.gov/dnav/pet/` on June 17, 2021. We use the "all grades, all formulations" prices.

We present the impulse response estimates for the city gasoline prices in Figures 4 (a) and (b). For ease of exposition, we split our sample of eight cities into two groups. The first group of cities includes Boston, New York City, Chicago and Cleveland. These cities form a natural group because they are located in the Petroleum Administration for Defence Districts (PADD), zones 1 and 2, which are the zones most closely linked via pipeline distribution to PADD 3, which encompasses the Gulf according to the EIA.[17] Thus, these cities would be most likely to experience a direct effect from a quantity supply shock in the Gulf. The second group of cities includes Denver, Los Angeles, San Francisco and Seattle. These cities are located in PADD zones 4 and 5 and are generally not closely linked to oil production in the Gulf. We do not include Houston or Miami in either group because it is plausible that these cities are directly affected by the hurricanes themselves. Conceptually, we want to separate the oil supply shock from the hurricane shock itself and thus we exclude Houston and Miami from our sample.

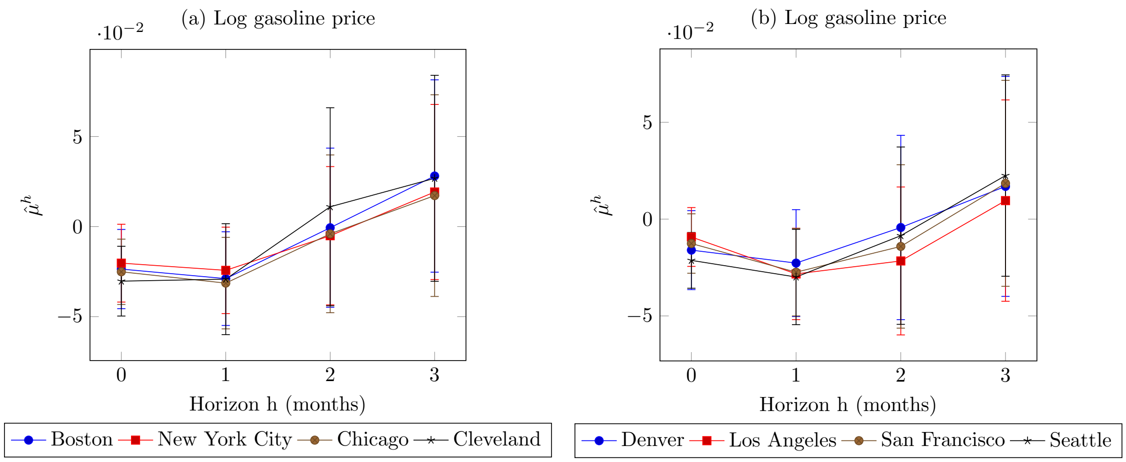
In the first group of cities plotted in Figure 4 (a), the impulse responses are roughly identical both in terms of the point estimates and the 95 percent confidence intervals indicated by the whisker lines. There is a price response in the current month and one month after the oil supply shock of roughly $\hat{\mu} = -0.02$ and $\hat{\mu} = -0.03$, respectively, which largely disappears by the second month after the shock. These point estimates are generally significantly different from zero. In contrast, the second group of cities plotted in Figure 4 (b) does not have a similar contemporaneous response although they do, in general, have a statistically significant response of roughly the same magnitude as the first group one month after the oil supply shock. The only exception is Denver, which does not have a significant impact at any horizon we examine. These impulse responses suggest that the impact of the oil supply shock is (mildly) heterogeneous for the cities we examine, and that the differences across cities may be due to infrastructure links. Assuming that oil prices are competitively priced, these results also suggest that either drawing down inventories is more costly for refiners than relying on flow production, or that gasoline price increases lead to greater inventory drawdowns. Our results are compatible with both mechanisms and do not further identify the causal channel.

2.4 State employment

We next turn to the question of whether oil supply shocks affect the broader US economy. Our interest is not whether hurricanes affect economic activity (see for instance, Stobl, 2011, and Deryugina, 2017), but whether disruptions to oil supply caused by hurricanes affect economic activity. To isolate the effect of the latter, we drop the PADD 3 states and the states directly bordering the Gulf (Florida, Alabama, Arkansas, Mississippi, Louisiana, Texas and New Mexico) from our estimation sample. For each of the remaining

[17] The PADD zones were established during WWII to administer the allocation of petroleum and other fuels during the war. These zones continue to exist today, and oil supply infrastructure such as pipelines is often organized by zone.

Figure 4: Response of city-level gasoline prices to oil supply shock ψ_t



Notes: ψ_t is the inverse hyperbolic sine transform of the percent oil supply shock Ψ_t. Whiskers indicate 95 percent confidence bands.

states in our sample, we estimate the effect of the oil supply shock on the natural logarithm of the state's employment. We do so separately by state, because it does not appear plausible to believe that (i) the effect of the oil supply shock is constant across states (especially given Figures 4 (a) and (b) and the fact that not all PADD districts are directly linked for oil distribution) or (ii) the stable unit treatment assumption is valid, since it would seem plausible that the effect in one state may affect the treatment in a neighbouring state. Moreover, the advantage in estimating a panel regression would be primarily, in this case, to increase the sample size, which does not appear necessary in our context, since we have roughly 360 observations by state.

We obtain employment data for the US states for the years 1991-2019 and estimate for each state n in our remaining sample of $N = 44$ states:[18]

$$y_{n,t+h} = \sum_{i=1}^{k} \rho_n^{i,h} y_{n,t-i} + X_t \beta_n^h + \mu_n^h \psi_{n,t} + e_{n,t+h}, \quad \forall n \in N, \tag{3}$$

where $y_{n,t+h}$ is the logarithm of employment at time $t+h$ with the coefficients and variables indexed by n but otherwise identical to those described in Equation (2). We set $k = 13$ and $h = \{0, 1, ..., 5\}$. Our interest is in the distribution of μ_n^h. We are primarily interested in two features of the distribution: the levels of $\hat{\mu}_n^h$ and the statistical significance of the estimates in terms of being different from zero. Given that we have 264 separate estimates of $\hat{\mu}_n^h$, we were initially concerned with how to present the estimates in a clear and effective manner. Fortunately, the empirical estimates rendered such concerns moot. Of the 264 estimates

[18]The state employment data were obtained from Haver (BLS) on June 11, 2021.

$\hat{\mu}_n^h$, only a single estimate is statistically significantly different from zero at the 5 percent significance level: Pennsylvania, at a horizon of three months. We are mindful that simply by random chance some of these estimates could satisfy statistical significance. Applying the Bonferroni correction renders this estimate not statistically significantly different from zero. Thus, there appears to be little statistical evidence that our measure of oil supply shocks affect employment at any horizon up to 5 months for any state.

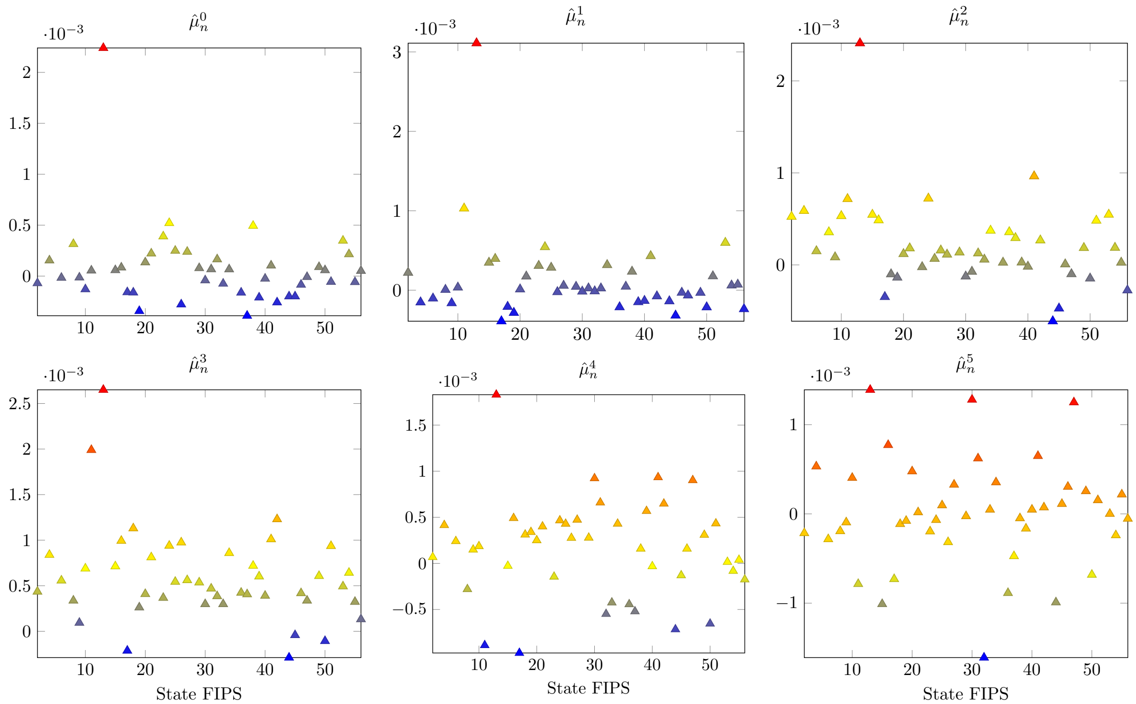
Although the point estimates may not be statistically significant, it is possible that their estimated magnitudes may still be of interest. As an example, if the point estimates were large but had high variance, this might suggest that our log-linear specification was not a reasonable specification for the data. Or, if the estimates were all close to zero, then this could be viewed as evidence that the effect of oil supply shocks on employment was actually likely zero and not simply difficult to estimate. Figure 5 plots the estimates of μ_n^h for $h = \{0, 1, ..., 5\}$ and each of the 44 states in our sample. The states are ordered by the value of their FIPS number (this is simply for convenience; any ordering is arbitrary). For all horizons, the estimates $\hat{\mu}_n^h$ are small in magnitude and in all cases less than 0.005 and typically less than 0.001. These are small elasticities and suggest that the employment response to an oil supply shock is negligible even in level terms. For $h = 0$ and $h = 1$, the estimates are generally almost exactly zero. The dispersion in the estimates does increase for higher values of h, but there is no evidence of a trend increase in the employment elasticity. We do note that there is one outlier in terms of the estimates at all horizons: the state of Georgia, which we include in our estimation sample, but it may also be directly affected by the hurricane paths themselves (perhaps via temporary migration from the predicted path of the storm). Only one conclusion from Figure 5 appears tenable: employment is unaffected by temporary oil supply shocks.

2.5 Production and oil supply shocks

We next examine the effect of oil supply shocks on production in the US using disaggregated industrial production data. We obtain non-seasonally adjusted industrial production indices by major industry for the period 1980-2019 from Table G17 published by the Federal Reserve Board.[19] We focus on both total industrial production and a subset of industries to provide a picture of how oil supply shocks may or may not be transmitted across sectors. While the industrial production data are disaggregated by industry, they are not disaggregated by geography, so we cannot ensure that the hurricane shocks do not directly impact production, rather than operating through their effect on oil supply. For example, Hurricane Katrina overwhelmed the levees protecting New Orleans and devastated the city, so to the extent that particular industries in New Orleans were significant producers of oil-based products, then Katrina likely had a direct effect on those indices. We discuss below how we trace out evidence both for and against a causal interpretation of oil supply shocks.

[19] The data were obtained from `https://www.federalreserve.gov/datadownload/Build.aspx?rel=g17` on October 15, 2021.

Figure 5: Response of state-level employment to oil supply shock ψ_t



Notes: Estimated effect on log employment for 44 US states, excluding the Florida, Alabama, Arkansas, Mississippi, Louisiana, Texas, and New Mexico. Each triangle represents a state. ψ_t is the inverse hyperbolic sine transform of the percent oil supply shock Ψ_t. $\hat{\mu}_n^h$ denotes the impact on state n at horizon h. State FIPS refers to the US Federal Information Processing Standards identifiers for each state.

We begin by examining industries that are likely to have been directly impacted by the oil supply shock: mining and mineral extraction (North American Industry Classification System (NAICS) 21), petroleum and coal production (NAICS 324), chemicals (NAICS 325) and plastics and rubber products (NAICS 326). These industries either produce oil (mining and mineral extraction) or use refined oil as an input for production.[20] Thus, hurricanes that directly affect oil production or refinement should affect these measures of industrial production if our oil supply shocks are, in fact, shocks. We note that apart from mining and mineral extraction, these indices are part of the non-durable manufacturing sub-component of manufacturing industrial production. Next, we examine industries that are not directly affected by oil production but which conceivably may be affected either because oil products are complements or substitutes: electric and gas utilities (NAICS 2211), non-metallic mineral products (NAICS 327), machinery (NAICS 333) and motor vehicles and parts (NAICS 33613). We note that apart from electric and gas utilities, these indices are part of the durable manufacturing sub-component of manufacturing industrial production.[21] Finally, we examine how oil supply shocks affect the total, manufacturing, durable manufacturing and non-durable manufacturing indices of industrial production. These indices include all the remaining sub-indices to assuage concerns that the data series chosen above were cherry-picked. These indices are also informative about possible indirect effects that may, perhaps, operate through consumer or final demand in addition to direct production input effects.

We estimate for each industrial production series s in our sample :

$$y_{s,t+h} = \sum_{i=1}^{k} \rho_n^{i,h} y_{n,t-i} + X_t \beta_n^h + \mu_n^h \psi_{n,t} + e_{n,t+h}, \quad \forall n \in N, \tag{4}$$

where the coefficients and variables are indexed by s but otherwise identical to those described in Equation (2). We set $k = 8$ but our estimates are unaffected by choices of higher values for k. We set $h = \{0, 1, ..., 5\}$ which implies that the number of observations for each regression range from 472 to 466. Figure 6 presents the impulse response estimates for the series described above.

Figure 6 (a) illustrates that the hurricane shocks directly affect oil production and refining as the mining and petroleum sub-indices are both statistically different from zero at the 95 percent level. Indeed, both series are nearly identical in terms of their impulse response functions until $h = 4$. Chemicals and plastics

[20]To map how oil is used in the US, we follow `https://www.eia.gov/energyexplained/oil-and-petroleum-products/use-of-oil.php`. While the vast majority of oil in the US is used as fuel, the seventh largest usage is petrochemical feedstock which is an input to chemicals and plastics. An alternative would be to follow Alquist, Bhattarai, and Coibion (2020) and use US input-output tables to link oil production to related industries. We choose not to follow this approach here for three reasons. The first reason is simply parsimony as the input output tables reported detailed data for 405 NAICS classifications. The second reason is that roughly 85 percent of oil extraction goes to refineries according to the latest I-O tables, and 75 percent of refinery output is final consumption by consumers (with a further almost 14 percent to commercial trucking). Since Alquist, Bhattarai, and Coibion (2020) consider commodities writ large and not just oil, this high network concentration is less relevant for their study. Finally, our interest is not just whether there is a direct effect on production but also an indirect effect via less consumer demand if price changes affect household budgets.

[21]Non-metallic mineral products include cement, glass and ceramics and are energy intensive to produce.

appear much less affected, although the point estimate for chemical production is statistically significant for $h = 0$, indicating a contemporaneous effect. It is not necessarily surprising that chemical manufacturing is affected by hurricanes in the Gulf, as the Gulf coast from Texas to the Florida panhandle is the location of many chemical producers in the US. There is no apparent effect from the hurricane shock on plastics and rubber product production in the US at any h we consider. Figure 6 (b) presents the impulse response estimates for products that might appear to be either complements or substitutes for oil production. For example, one might expect motor vehicle and parts production to slow if increasing gasoline prices were expected to lower the demand for motors or their usage. One might also suspect, since machinery and non-metallic mineral products are energy intensive, that an oil supply shock would lower their production. One might also expect electricity and gas demand to be affected to the extent that an energy shortfall from lost oil production could be offset by other energy sources. The impulse responses in Figure 6 (b) are not statistically different from zero at the 95 percent level of significance and, perhaps more relevantly, are flat, which suggests that the oil supply shock does not propagate across the broader set of US industries. The impulse responses in Figures 6 (a) and (b) suggest that oil supply shocks are localized to their own industry and do not spill over into the broader economy. This result is consistent with Lee and Ni (2002) and Jo, Karnizova, and Reza (2019), who find that only a small set of oil-related sectors experience oil price shocks as supply shocks.

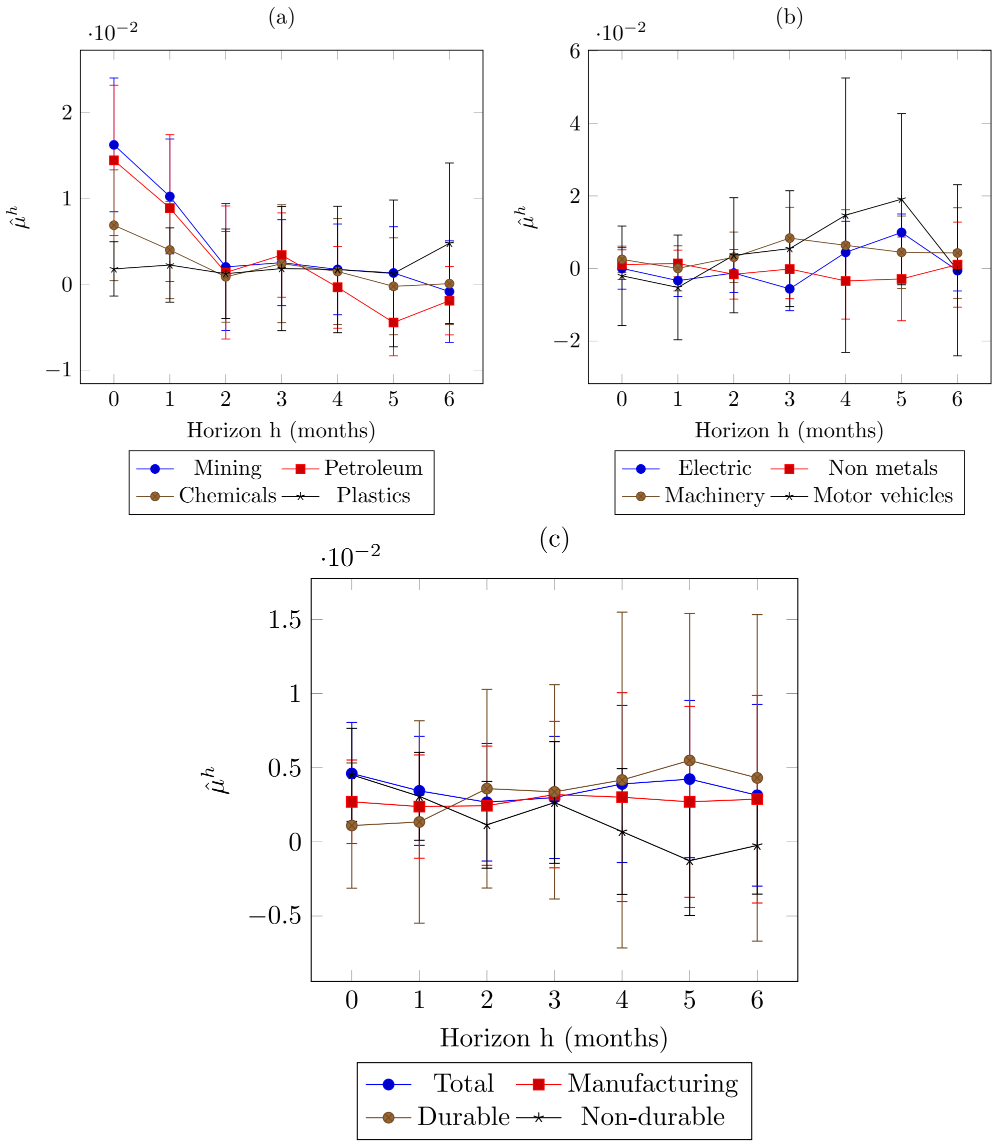
To gauge the overall effect of the supply shocks on industrial production, Figure 6 (c) shows the impulse responses for the total, durable and non-durable manufacturing industrial production indices. The impulse responses for the total and non-durable indices are statistically significant for $h = 0, 1$ and almost identical in terms of their point estimates because mining and petroleum production are elements of both indices. However, these effects are short-lived and the point estimates are roughly 1/3 of the point estimates for either mining or petroleum production, which suggests that the effects are not broadly similar over the remaining component sub-indices. Moreover, the manufacturing sub-index, which includes both durable and non-durable production, is not statistically different from zero and is essentially flat. This suggests that the remaining non-durable and durable sub-indices are not significantly affected by the oil supply shock.[22] The impulse responses in Figure 6 imply that oil supply shocks are localized to their industry and do not broadly affect US aggregate production. This conclusion is consistent with our estimates for state employment.

2.6 Inflation

The short-run industrial production responses to the oil supply shocks suggest that there may be some reduction in supply of goods produced in the US economy. Although there is little evidence that these shocks

[22] The difference between the total index and the manufacturing index is largely due to the mining and mineral extraction index.

Figure 6: Response of industrial production to oil supply shock ψ_t



Notes: Estimated effect on log industrial production. ψ_t is the inverse hyperbolic sine transform of the percent oil supply shock Ψ_t. Whiskers indicate 95 percent confidence bands.

propagate to sectors of the economy not directly affected, one might expect that a reduction in industrial production would increase prices. Indeed, our previous exercises provided evidence that temporary oil supply shocks affect gasoline prices. We now turn to the question of whether these shocks also affect the broader price level.

We use monthly data on the consumer price index from the US Bureau of Labor Statistics (BLS) for the US and the four main regions reported by the BLS: the Northeast, the Midwest, the South and the West.[23] We focus on three price level measures: the total CPI, the energy sub-index of the CPI, and the non-energy sub-index of the CPI. We use the logarithm of each index as our dependent variable and estimate our baseline specification, Equation (2), with $k = 12$ and $h = \{0, 1, ..., 8\}$.

Figure 7 plots the impulse responses for the logarithms of the three price level series for each of the five geographies. The impulse responses for the CPI and the energy sub-index of the CPI are similar to those of the city-level gasoline prices we report above. The point estimates are significant at the 5 percent level for the US and the South for the CPI for $h = 0$ and for the South for the energy sub-index. The remaining point estimates for the CPI and energy sub-index are not statistically significant at any horizon. Interestingly, we find no evidence of statistically significant point estimates for the non-energy sub-index for any region for horizons up to $h = 3$. However, we do find statistically significant point estimates at the 5 percent level for the Northeast region for $h = 4$. We are reluctant to conclude that this is strong evidence of price pass-through, given that there is no evidence of a similar pattern in the total CPI impulse response.

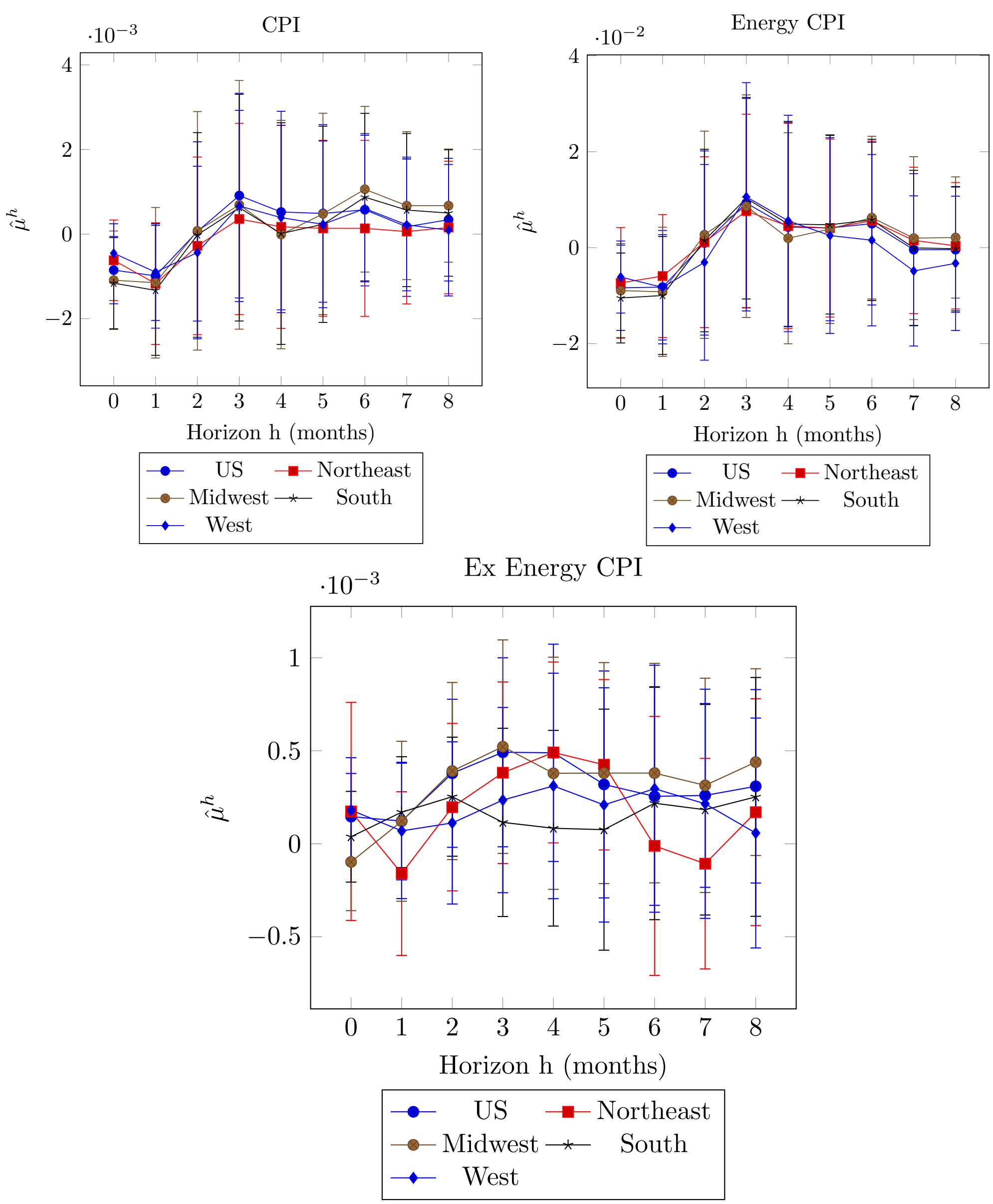
The evidence from the impulse responses plotted in Figure 7 appears to support a conclusion that oil supply shocks are transitory and localized to a narrow subset of industries directly involved in oil production. Broader effects for the US economy are effectively nominal shocks to prices and, even here, appear to be both muted and transitory.

2.7 Export and imports

Our final consideration is to examine the effect of oil supply shocks on international trade and finance. One plausible reason why we might find no effect from oil supply shocks in the Gulf is that lost oil production is replaced by oil imports, so that there is, in fact, no change in the quantity of oil available to the US economy. Since Canada is an oil-producing neighbour to the US, it is perhaps possible that oil shocks in the Gulf lead to increased oil supply by Canadian producers. Although this might seem unlikely since our measure of oil supply shocks in the Gulf did not appear to affect the EIA measures of imported oil prices, it is plausible that fixed-price contracts denominated in USD might mitigate against price impacts. To analyze whether the oil supply shock in the Gulf transmits as a positive oil supply shock to Canadian producers, we use

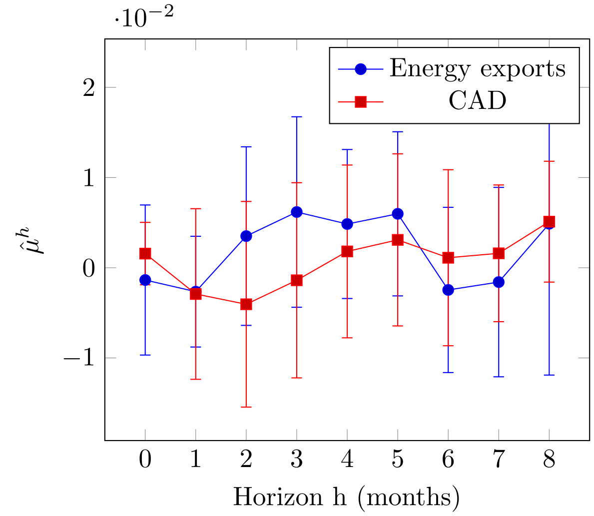
[23] The data were obtained from `https://data.bls.gov/cgi-bin/dsrv` on November 10, 2021.

Figure 7: Response of consumer price index to oil supply shock ψ_t



Estimated effect on log CPI. ψ_t is the inverse hyperbolic sine transform of the percent oil supply shock Ψ_t. Whiskers indicate 95 percent confidence bands.

Figure 8: Response of Canadian energy exports and exchange rate to oil supply shock ψ_t



Estimated effect on log CAD/USD exchange rate and real Canadian energy exports. ψ_t is the inverse hyperbolic sine transform of the percent oil supply shock Ψ_t. Whiskers indicate 95 percent confidence bands.

Canadian real energy exports for the years 1997-2019 and the Canadian dollar exchange rate for the years 1980-2019.[24]

We estimate using our baseline specification, Equation (2), with $k = 12$ and $h = \{0, 1, ..., 8\}$. Figure 8 presents the impulse response estimates for the natural logarithms of the Canadian real energy exports and the exchange rate. The impulse response estimates are not significantly different from zero at any horizon we consider. Taken together, Figures 2, 4 and 8 suggest that oil supply shocks in the Gulf may increase gasoline prices over the very short (up to one month) horizon, which is not offset by changes in imported oil demand. Finally, there is little evidence that the oil supply shock in the Gulf affected the Canada-US exchange rate at any horizon.

3 Conclusion

We have used a quasi-random weather event, hurricanes, which lead to production shut-ins at offshore oil platforms in the Gulf to investigate the effect of oil supply shocks. We show that these hurricane events are associated with lower oil production in the Gulf and that the magnitude of these production changes can account for up to 20 percent of US production. We analyze the effects of these oil supply shocks for oil prices, gasoline prices, employment, industrial production and international trade and finance. We find

[24]The data were obtained from Statistics Canada, series V7T83955, and the Bank of Canada, series V37426, respectively on 3/9/2021.

little evidence that temporary oil supply shocks transmit to the broader US economy or to its international trading partner Canada.

References

Alquist, R., S. Bhattarai, and O. Coibion (2020): "Commodity-Price Comovement and Global Economic Activity," *Journal of Monetary Economics*, 112, 41–56.

Anderson, S. T., R. Kellogg, and S. W. Salant (2018): "Hotelling under Pressure," *Journal of Political Economy*, 126(3), 984–1026.

Baumeister, C., and J. D. Hamilton (2019): "Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks," *American Economic Review*, 109(5), 1873–1910.

Bellemare, M. F., and C. J. Wichman (2020): "Elasticities and the Inverse Hyperbolic Sine Transformation," *Oxford Bulletin of Economics and Statistics*, 82(1), 50–61.

Bjørnland, H. C., F. M. Nordvik, and M. Rohrer (2021): "Supply Flexibility in the Shale Patch: Evidence from North Dakota," *Journal of Applied Econometrics*, 36(3), 273–292.

Brannlund, J., G. Dunbar, R. Ellwanger, and M. Krutkiewicz (2022): "Weather the Storms? Hurricanes, Technology and Oil Production," Discussion Paper 2022-36, Bank of Canada Staff Working Paper.

Caldara, D., M. Cavallo, and M. Iacoviello (2019): "Oil Price Elasticities and Oil Price Fluctuations," *Journal of Monetary Economics*, 103, 1–20.

de Chaisemartin, C., and X. D'Haultfœuille (2020): "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, 110(9), 2964–96.

Deryugina, T. (2017): "The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance," *American Economic Journal: Economic Policy*, 9(3), 168–98.

Dunbar, G., W. Steingress, and B. Tomlin (2022): "Climate Variability and International Trade," Discussion Paper 2022-XX, mimeo.

Herbst, E. P., and B. K. Johannsen (2020): "Bias in Local Projections," Finance and Economics Discussion Series 2020-010, Board of Governors of the Federal Reserve System.

Herrera, A. M., and S. K. Rangaraju (2020): "The Effect of Oil Supply Shocks on US Economic Activity: What Have We Learned," *Journal of Applied Econometrics*, 35(2), 141–159.

Hwang, J. T. (1986): "Multiplicative Errors-in-Variables Models with Applications to Recent Data Released by the U.S. Department of Energy," *Journal of the American Statistical Association*, 81(395), 680–688.

Jo, S., L. Karnizova, and A. Reza (2019): "Industry Effects of Oil Price Shocks: A Re-Examination," *Energy Economics*, 82, 179–190.

Jordá, O. (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95(1), 161–182.

Känzig, D. R. (2021): "The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements," *American Economic Review*, 111(4), 1092–1125.

Kilian, L. (2009): "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *American Economic Review*, 99(3), 1053–69.

——— (2010): "Explaining Fluctuations in Gasoline Prices: A Joint Model of the Global Crude Oil Market and the U.S. Retail Gasoline Market," *The Energy Journal*, 31(2), 87–112.

Kilian, L., and D. P. Murphy (2014): "The Role of Inventories and Speculative Tracing in the Global Market for Crude Oil," *Journal of Applied Econometrics*, 29(3), 454–478.

Kilian, L., and X. Zhou (2020a): "Does Drawing down the U.S. Strategic Petroleum Reserve Help Stabilize Oil Prices," *Journal of Applied Econometrics*, 35, 673–691.

Kilian, L., and X. Zhou (2020b): "The Econometrics of Oil Market VAR Models," Working Papers 2006, Federal Reserve Bank of Dallas.

Knapp, K. R., H. J. Diamond, J. P. Kossin, M. C. Kruk, and C. J. Schreck (2018): "International Best Track Archive for Climate Stewardship (IBTrACS) Project, Version 4, since 1980," Accessed in December 2020.

Knapp, K. R., M. C. Kruk, D. H. Levinson, H. J. Diamond, and C. J. Neumann (2010): "The International Best Track Archive for Climate Stewardship (IBTrACS): Unifying tropical cyclone best track data," *Bulletin of the American Meteorological Society*, 91, 363–376.

Lee, K., and S. Ni (2002): "On the Dynamic Effects of Oil Price Shocks: a Study using Industry Level Data," *Journal of Monetary Economics*, 49(4), 823–852.

Montiel Olea, J. L., and M. Plagborg-Møller (2021): "Local Projection Inference is Simpler and More Robust Than You Think," *Econometrica*, 89(4), 1789–1823.

Newell, R. G., and B. C. Prest (2017): "The Unconventional Oil Supply Boom: Aggregate Price Response from Microdata," Working Paper 23973, National Bureau of Economic Research.

Pindyck, R. S. (1994): "Inventories and the Short-Run Dynamics of Commodity Prices," *The RAND Journal of Economics*, 25(1), 141–159.

Plagborg-Møller, M., and C. Wolf (2021): "Local Projections and VARs Estimate the Same Impulse Responses," *Econometrica*, 89(2), 955–980.

Stobl, E. (2011): "The Economic Growth Impact of Hurricanes: Evidence from US Coastal Counties," *Review of Economics and Statistics*, 93(2), 575–589.

Working, H. (1949): "The Theory of Price of Storage," *The American Economic Review*, 39(6), 1254–1262.

4 Appendix: Detailed regression results

Table 1: Imported oil prices

	(a) Dependent variable: ln(real oil prices)								
Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ψ	-0.001	0.008	0.027	0.042	0.019	0.001	-0.016	-0.032	-0.022
	[0.007]	[0.013]	[0.020]	[0.029]	[0.030]	[0.030]	[0.023]	[0.020]	[0.018]
Lags	12	12	12	12	12	12	12	12	12
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	468	468	468	468	468	468	468	468	468
R^2	0.99	0.96	0.94	0.93	0.91	0.91	0.91	0.92	0.92
	(b) Dependent variable: ln(nominal oil prices)								
Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ψ	-0.002	0.008	0.028	0.043	0.020	0.001	-0.015	-0.031	-0.021
	[0.007]	[0.014]	[0.021]	[0.030]	[0.031]	[0.031]	[0.023]	[0.020]	[0.018]
Lags	12	12	12	12	12	12	12	12	12
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	468	468	468	468	468	468	468	468	468
R^2	0.99	0.98	0.96	0.95	0.94	0.94	0.94	0.95	0.95

Notes: Robust standard errors in parentheses: ***, **, * indicate the statistically significant difference from zero at the 0.1, 1 and 5 percent levels respectively.

Table 2: Imported oil prices, excluding hurricanes Katrina, Rita, Gustav and Ike

	(a) Dependent variable: ln(real oil prices)								
Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ψ	-0.005	-0.009	-0.002	0.009	-0.011	-0.036	-0.037	-0.042	-0.019
	[0.009]	[0.011]	[0.014]	[0.022]	[0.029]	[0.030]	[0.025]	[0.022]	[0.024]
Lags	12	12	12	12	12	12	12	12	12
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	466	466	466	466	466	466	466	466	466
R^2	0.99	0.96	0.95	0.93	0.91	0.91	0.91	0.92	0.92
	(b) Dependent variable: ln(nominal oil prices)								
Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ψ	-0.005	-0.009	-0.002	0.009	-0.011	-0.036	-0.037	-0.043	-0.019
	[0.009]	[0.011]	[0.014]	[0.023]	[0.030]	[0.031]	[0.026]	[0.022]	[0.025]
Lags	12	12	12	12	12	12	12	12	12
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	466	466	466	466	466	466	466	466	466
R^2	0.99	0.98	0.97	0.96	0.94	0.94	0.95	0.95	0.95

Notes: Robust standard errors in parentheses: ***, **, * indicate the statistically significant difference from zero at the 0.1, 1 and 5 percent levels respectively.

Table 3: Inventory responses

	(a) Dependent variable: US refinery inventories								
Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\tilde{\Psi}$	0.612**	0.506*	0.304	0.003	-0.163	-0.285	-0.247	-0.249	0.002
	[0.195]	[0.235]	[0.211]	[0.236]	[0.245]	[0.377]	[0.270]	[0.262]	[0.277]
Observations	437	437	437	437	437	437	437	437	437
R^2	0.99	0.97	0.96	0.95	0.95	0.94	0.94	0.95	0.95
Lags	12	12	12	12	12	12	12	12	12
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	(b) Dependent variable: SPR inventories								
Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\tilde{\Psi}$	0.120*	0.294**	0.288**	0.286**	0.298**	0.257*	0.220*	0.096	-0.013
	[0.047]	[0.102]	[0.105]	[0.096]	[0.099]	[0.101]	[0.091]	[0.108]	[0.119]
Observations	437	437	437	437	437	437	437	437	437
R^2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Lags	12	12	12	12	12	12	12	12	12
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses: ***, **, * indicate the statistically significant difference from zero at the 0.1, 1 and 5 percent levels respectively.

Table 4: Inventory responses, excluding hurricanes Katrina, Rita, Gustav and Ike

(a) Dependent variable: US refinery inventories

Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\tilde{\Psi}$	1.391***	1.289***	0.789	0.629	0.415	0.422	0.321	0.234	0.536
	[0.272]	[0.373]	[0.545]	[0.575]	[0.468]	[0.542]	[0.614]	[0.592]	[0.627]
Observations	435	435	435	435	435	435	435	435	435
R^2	0.99	0.97	0.96	0.95	0.95	0.94	0.94	0.95	0.95
Lags	12	12	12	12	12	12	12	12	12
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(b) Dependent variable: SPR inventories

Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\tilde{\Psi}$	-0.003	0.121	0.170	0.208	0.169	0.092	0.113	0.123	0.061
	[0.041]	[0.086]	[0.125]	[0.130]	[0.149]	[0.161]	[0.167]	[0.176]	[0.179]
Observations	435	435	435	435	435	435	435	435	435
R^2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Lags	12	12	12	12	12	12	12	12	12
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses: ***, **, * indicate the statistically significant difference from zero at the 0.1, 1 and 5 percent levels respectively.

Table 5: City gasoline prices

Horizon (h)		(0)	(1)	(2)	(3)
ψ	Boston	-0.024*	-0.029*	-0.001	0.028
		[0.011]	[0.013]	[0.022]	[0.027]
Observations		193	193	193	193
R^2		0.96	0.88	0.80	0.77
ψ	Chicago	-0.025**	-0.031*	-0.004	0.017
		[0.009]	[0.013]	[0.022]	[0.028]
Observations		229	229	229	229
R^2		0.97	0.92	0.90	0.89
ψ	Cleveland	-0.030**	-0.029	0.011	0.027
		[0.010]	[0.015]	[0.028]	[0.029]
Observations		193	193	193	193
R^2		0.93	0.84	0.79	0.75
ψ	New York	-0.020	-0.024*	-0.005	0.019
		[0.011]	[0.012]	[0.019]	[0.024]
Observations		229	229	229	229
R^2		0.98	0.94	0.90	0.89
ψ	Denver	-0.016	-0.023	-0.004	0.017
		[0.010]	[0.014]	[0.024]	[0.028]
Observations		229	229	229	229
R^2		0.97	0.92	0.89	0.87
ψ	LA	-0.009	-0.028*	-0.022	0.010
		[0.008]	[0.012]	[0.019]	[0.026]
Observations		229	229	229	229
R^2		0.97	0.94	0.91	0.90
ψ	San Francisco	-0.013	-0.027*	-0.014	0.019
		[0.008]	[0.011]	[0.021]	[0.027]
Observations		229	229	229	229
R^2		0.97	0.93	0.91	0.89
ψ	Seattle	-0.021**	-0.030*	-0.009	0.022
		[0.007]	[0.012]	[0.023]	[0.026]
Observations		193	193	193	193
R^2		0.96	0.89	0.83	0.79
Lags		6	6	6	6
Month FE		Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses: ***, **, * indicate the statistically significant difference from zero at the 0.1, 1 and 5 percent levels respectively.

Table 6: State employment

Horizon (h)		(0)	(1)	(2)	(3)	(4)	(5)
ψ	Alaska	-0.000	0.000	0.001	0.000	0.000	-0.000
		[0.000]	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.99
ψ	Arizona	0.000	-0.000	0.001	0.001	0.000	0.001
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	1.00	1.00
ψ	California	-0.000	-0.000	0.000	0.001	0.000	-0.000
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.98
ψ	Colorado	0.000	0.000	0.000	0.000	-0.000	-0.000
		[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	1.00	0.99
ψ	Delaware	-0.000	0.000	0.001	0.001	0.000	0.000
		[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.98
ψ	District of Columbia	0.000	0.001	0.001	0.002	-0.001	-0.001
		[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.99
ψ	Georgia	0.002	0.003	0.002	0.003	0.002	0.001
		[0.001]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.99
ψ	Hawaii	0.000	0.000	0.001	0.001	-0.000	-0.001
		[0.000]	[0.001]	[0.001]	[0.001]	[0.002]	[0.003]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	0.99	0.99	0.94	0.90
ψ	Idaho	0.000	0.000	0.000	0.001	0.000	0.001
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	1.00	1.00
ψ	Illinois	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001
		[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347

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Table 6 – continued from previous page

Horizon (h)		(0)	(1)	(2)	(3)	(4)	(5)
R^2		0.99	0.99	0.98	0.98	0.89	0.85
ψ	Indiana	-0.000	-0.000	-0.000	0.001	0.000	-0.000
		[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347
R^2		1.00	0.99	0.99	0.99	0.94	0.92
ψ	Iowa	-0.000	-0.000	-0.000	0.000	0.000	-0.000
		[0.000]	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		0.99	0.99	0.99	0.99	0.96	0.94
ψ	Kansas	0.000	0.000	0.000	0.000	0.000	0.000
		[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	0.99	0.98	0.97
ψ	Kentucky	0.000	0.000	0.000	0.001	0.000	0.000
		[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	0.99	0.99	0.99	0.97	0.96
ψ	Maine	0.000	0.000	-0.000	0.000	-0.000	-0.000
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	0.99	0.99	0.99	0.97	0.96
ψ	Maryland	0.001	0.001	0.001	0.001	0.000	-0.000
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.98
ψ	Massachusetts	0.000	0.000	0.000	0.001	0.000	0.000
		[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	0.99	0.94	0.92
ψ	Michigan	-0.000	-0.000	0.000	0.001	0.000	-0.000
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	0.99	0.99	0.90	0.86
ψ	Minnesota	0.000	0.000	0.000	0.001	0.000	0.000
		[0.000]	[0.000]	[0.001]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.98
ψ	Missouri	0.000	0.000	0.000	0.001	0.000	-0.000
		[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347

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Table 6 – continued from previous page

Horizon (h)		(0)	(1)	(2)	(3)	(4)	(5)
R^2		1.00	1.00	1.00	1.00	0.97	0.95
ψ	Montana	-0.000	-0.000	-0.000	0.000	0.001	0.001
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.99
ψ	Nebraska	0.000	0.000	-0.000	0.000	0.001	0.001
		[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.99
ψ	Nevada	0.000	-0.000	0.000	0.000	-0.001	-0.002
		[0.000]	[0.000]	[0.001]	[0.001]	[0.002]	[0.003]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.99
ψ	New Hampshire	-0.000	0.000	0.000	0.000	-0.000	0.000
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.98	0.97
ψ	New Jersey	0.000	0.000	0.000	0.001	0.000	0.000
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	0.99	0.99	0.99	0.95	0.92
ψ	New York	-0.000	-0.000	0.000	0.000	-0.000	-0.001
		[0.000]	[0.000]	[0.001]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	0.99	0.99	0.99	0.93	0.89
ψ	North Carolina	-0.000	0.000	0.000	0.000	-0.001	-0.000
		[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.98
ψ	North Dakota	0.000	0.000	0.000	0.001	0.000	-0.000
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.99
ψ	Ohio	-0.000	-0.000	0.000	0.001	0.001	-0.000
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347
R^2		0.99	0.99	0.98	0.98	0.88	0.85
ψ	Oklahoma	-0.000	-0.000	-0.000	0.000	-0.000	0.000
		[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347

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Table 6 – continued from previous page

Horizon (h)		(0)	(1)	(2)	(3)	(4)	(5)
R^2		1.00	1.00	1.00	1.00	0.99	0.98
ψ	Oregon	0.000	0.000	0.001	0.001	0.001	0.001
		[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.99
ψ	Pennsylvania	-0.000	-0.000	0.000	0.001*	0.001	0.000
		[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		0.99	0.99	0.99	0.99	0.94	0.92
ψ	Rhode Island	-0.000	-0.000	-0.001	-0.000	-0.001	-0.001
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347
R^2		1.00	0.99	0.99	0.99	0.93	0.88
ψ	South Carolina	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
		[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.99
ψ	South Dakota	-0.000	-0.000	0.000	0.000	0.000	0.000
		[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	1.00	1.00
ψ	Tennessee	-0.000	-0.000	-0.000	0.000	0.001	0.001
		[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	0.99	0.98	0.97
ψ	Utah	0.000	-0.000	0.000	0.001	0.000	0.000
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	1.00	1.00
ψ	Vermont	0.000	-0.000	-0.000	-0.000	-0.001	-0.001
		[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	0.99	0.99	0.98	0.97
ψ	Virginia	-0.000	0.000	0.000	0.001	0.000	0.000
		[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	0.99	0.99
ψ	Washington	0.000	0.001	0.001	0.000	0.000	0.000
		[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347

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Table 6 – continued from previous page

Horizon (h)		(0)	(1)	(2)	(3)	(4)	(5)
R^2		1.00	1.00	1.00	1.00	0.99	0.99
ψ	West Virginia	0.000	0.000	0.000	0.001	-0.000	-0.000
		[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		0.99	0.98	0.98	0.98	0.89	0.86
ψ	Wisconsin	-0.000	0.000	0.000	0.000	0.000	0.000
		[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	0.99	0.99	0.99	0.96	0.95
ψ	Wyoming	0.000	-0.000	-0.000	0.000	-0.000	-0.000
		[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
Observations		347	347	347	347	347	347
R^2		1.00	1.00	1.00	1.00	1.00	1.00
Lags		13	13	13	13	13	13
Month FE		Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses: ***, **, * indicate the statistically significant difference from zero at the 0.1, 1 and 5 percent levels respectively.

Table 7: Industrial production

Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)
			Mining				
ψ	0.016***	0.010**	0.002	0.003	0.002	0.001	-0.001
	[0.004]	[0.003]	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]
Observations	472	471	470	469	468	467	466
R^2	0.98	0.97	0.96	0.96	0.95	0.95	0.95
			Petroleum				
ψ	0.014**	0.009*	0.001	0.003	-0.000	-0.004*	-0.002
	[0.004]	[0.004]	[0.004]	[0.002]	[0.002]	[0.002]	[0.002]
Observations	472	471	470	469	468	467	466
R^2	0.98	0.98	0.98	0.98	0.98	0.98	0.98
			Chemical				
ψ	0.007*	0.004	0.001	0.002	0.001	-0.000	0.000
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]
Observations	472	471	470	469	468	467	466
R^2	1.00	0.99	0.99	0.99	0.99	0.99	0.99
			Plastics				

Continued on next page

Table 7 – continued from previous page

Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)
ψ	0.002	0.002	0.001	0.002	0.002	0.001	0.005
	[0.002]	[0.002]	[0.003]	[0.004]	[0.004]	[0.004]	[0.005]
Observations	472	471	470	469	468	467	466
R^2	1.00	1.00	1.00	1.00	0.99	0.99	0.99
Electric and gas							
ψ	0.000	-0.003	-0.001	-0.006	0.004	0.010***	-0.001
	[0.003]	[0.002]	[0.003]	[0.003]	[0.004]	[0.003]	[0.003]
Observations	472	471	470	469	468	467	466
R^2	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Non metals							
ψ	0.001	0.001	-0.002	-0.000	-0.003	-0.003	0.001
	[0.002]	[0.002]	[0.003]	[0.004]	[0.005]	[0.006]	[0.006]
Observations	472	471	470	469	468	467	466
R^2	0.99	0.99	0.98	0.98	0.98	0.97	0.97
Machinery							
ψ	0.002	0.000	0.003	0.008*	0.006	0.004	0.004
	[0.002]	[0.003]	[0.003]	[0.004]	[0.005]	[0.005]	[0.006]
Observations	472	471	470	469	468	467	466
R^2	0.99	0.98	0.98	0.97	0.97	0.97	0.96
Motor vehicles							
ψ	-0.002	-0.005	0.004	0.005	0.015	0.019	-0.000
	[0.007]	[0.007]	[0.008]	[0.008]	[0.019]	[0.012]	[0.012]
Observations	472	471	470	469	468	467	466
R^2	0.97	0.96	0.96	0.96	0.96	0.96	0.97
Total							
ψ	0.005**	0.003	0.003	0.003	0.004	0.004	0.003
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]	[0.003]
Observations	472	471	470	469	468	467	466
R^2	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Manufacturing							
ψ	0.003	0.002	0.002	0.003	0.003	0.003	0.003
	[0.001]	[0.002]	[0.002]	[0.002]	[0.004]	[0.003]	[0.004]
Observations	472	471	470	469	468	467	466
R^2	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Durable							
ψ	0.001	0.001	0.004	0.003	0.004	0.005	0.004
	[0.002]	[0.003]	[0.003]	[0.004]	[0.006]	[0.005]	[0.005]
Observations	472	471	470	469	468	467	466

Continued on next page

Table 7 – continued from previous page

Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)
R^2	1.00	1.00	1.00	1.00	1.00	1.00	1.00
				Non-durable			
ψ	0.005**	0.003*	0.001	0.003	0.001	-0.001	-0.000
	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]
Observations	472	471	470	469	468	467	466
R^2	1.00	0.99	0.99	0.99	0.99	0.99	0.99
Lags	8	8	8	8	8	8	8
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses: ***, **, * indicate the statistically significant difference from zero at the 0.1, 1 and 5 percent levels respectively.

Table 8: Consumer Price Index

Horizon (h)		(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ψ	Midwest	-0.0011	-0.0012	0.000077	0.00069	-0.000011	0.00048	0.0011	0.00067	0.00067
		[0.00058]	[0.00089]	[0.0014]	[0.0015]	[0.0013]	[0.0012]	[0.00098]	[0.00087]	[0.00067]
Observations		385	384	383	382	381	380	379	378	377
R^2		1.000	1.000	0.999	0.999	0.999	0.999	0.999	0.999	0.999
ψ	Northeast	-0.00062	-0.0012	-0.00028	0.00036	0.00017	0.00014	0.00014	0.000061	0.00016
		[0.00048]	[0.00072]	[0.0010]	[0.0011]	[0.0012]	[0.0010]	[0.0010]	[0.00086]	[0.00078]
Observations		385	384	383	382	381	380	379	378	377
R^2		1.000	1.000	1.000	1.000	0.999	0.999	0.999	1.000	1.000
ψ	South	-0.0012*	-0.0013	-0.000020	0.00062	0.000013	0.00023	0.00087	0.00057	0.00050
		[0.00054]	[0.00077]	[0.0012]	[0.0013]	[0.0013]	[0.0012]	[0.00099]	[0.00090]	[0.00075]
Observations		385	384	383	382	381	380	379	378	377
R^2		1.000	1.000	1.000	0.999	0.999	0.999	0.999	0.999	0.999
ψ	US	-0.00085*	-0.00099	0.000064	0.00091	0.00052	0.00049	0.00058	0.00017	0.00034
		[0.00040]	[0.00062]	[0.0011]	[0.0012]	[0.0012]	[0.0011]	[0.00090]	[0.00082]	[0.00072]
Observations		468	467	466	465	464	463	462	461	460
R^2		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ψ	West	-0.00045	-0.00090	-0.00044	0.00066	0.00039	0.00023	0.00060	0.00022	0.000092
		[0.00035]	[0.00057]	[0.0010]	[0.0011]	[0.0011]	[0.00098]	[0.00087]	[0.00078]	[0.00078]
Observations		385	384	383	382	381	380	379	378	377
R^2		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Lags		12	12	12	12	12	12	12	12	12
Month FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses: ***, **, * indicate the statistically significant difference from zero at the 0.1, 1 and 5 percent levels respectively.

Table 9: Consumer Price Index – Energy

Horizon (h)		(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ψ	Midwest	-0.0090	-0.0092	0.0027	0.0086	0.0020	0.0039	0.0063	0.0020	0.0021
		[0.0049]	[0.0067]	[0.011]	[0.012]	[0.011]	[0.0098]	[0.0085]	[0.0085]	[0.0063]
Observations		468	467	466	465	464	463	462	461	460
R^2		0.995	0.988	0.985	0.982	0.980	0.979	0.981	0.983	0.985
ψ	Northeast	-0.0073	-0.0059	0.0012	0.0076	0.0045	0.0041	0.0056	0.0015	0.00039
		[0.0058]	[0.0064]	[0.0089]	[0.010]	[0.011]	[0.0093]	[0.0083]	[0.0076]	[0.0066]
Observations		468	467	466	465	464	463	462	461	460
R^2		0.997	0.993	0.989	0.987	0.985	0.984	0.985	0.986	0.988
ψ	South	-0.010*	-0.0100	0.0015	0.010	0.0049	0.0048	0.0058	-0.000050	-0.00022
		[0.0047]	[0.0061]	[0.0095]	[0.010]	[0.011]	[0.0093]	[0.0084]	[0.0081]	[0.0065]
Observations		468	467	466	465	464	463	462	461	460
R^2		0.996	0.990	0.986	0.984	0.981	0.980	0.982	0.984	0.986
ψ	US	-0.0084	-0.0082	0.00096	0.0093	0.0043	0.0041	0.0050	-0.00043	-0.00043
		[0.0044]	[0.0059]	[0.0096]	[0.011]	[0.011]	[0.0097]	[0.0085]	[0.0079]	[0.0065]
Observations		468	467	466	465	464	463	462	461	460
R^2		0.997	0.992	0.988	0.986	0.983	0.983	0.984	0.986	0.988
ψ	West	-0.0061	-0.0083	-0.0031	0.011	0.0056	0.0025	0.0016	-0.0049	-0.0033
		[0.0038]	[0.0055]	[0.010]	[0.012]	[0.011]	[0.010]	[0.0089]	[0.0078]	[0.0070]
Observations		468	467	466	465	464	463	462	461	460
R^2		0.997	0.992	0.989	0.988	0.986	0.985	0.986	0.988	0.990
Lags		12	12	12	12	12	12	12	12	12
Month FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses: ***, **, * indicate the statistically significant difference from zero at the 0.1, 1 and 5 percent levels respectively.

Table 10: Consumer Price Index – Excluding energy

Horizon (h)		(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ψ	Midwest	-0.000098	0.00012	0.00039	0.00052	0.00038	0.00038	0.00038	0.00031	0.00044
		[0.00013]	[0.00022]	[0.00024]	[0.00029]	[0.00031]	[0.00030]	[0.00030]	[0.00029]	[0.00025]
Observations		385	384	383	382	381	380	379	378	377
R^2		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ψ	Northeast	0.00017	-0.00016	0.00020	0.00038	0.00049*	0.00042	-0.000011	-0.00011	0.00017
		[0.00029]	[0.00022]	[0.00022]	[0.00024]	[0.00024]	[0.00023]	[0.00035]	[0.00028]	[0.00031]
Observations		385	384	383	382	381	380	379	378	377
R^2		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ψ	South	0.000038	0.00017	0.00025	0.00011	0.000083	0.000076	0.00022	0.00018	0.00025
		[0.00012]	[0.00015]	[0.00016]	[0.00025]	[0.00026]	[0.00032]	[0.00031]	[0.00028]	[0.00032]
Observations		385	384	383	382	381	380	379	378	377
R^2		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ψ	US	0.00015	0.00012	0.00038	0.00049	0.00049	0.00032	0.00025	0.00026	0.00031
		[0.00012]	[0.00016]	[0.00020]	[0.00025]	[0.00029]	[0.00030]	[0.00029]	[0.00025]	[0.00026]
Observations		468	467	466	465	464	463	462	461	460
R^2		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ψ	West	0.00018	0.000069	0.00011	0.00024	0.00031	0.00021	0.00030	0.00022	0.000058
		[0.00014]	[0.00018]	[0.00022]	[0.00025]	[0.00030]	[0.00031]	[0.00033]	[0.00031]	[0.00031]
Observations		385	384	383	382	381	380	379	378	377
R^2		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Lags		12	12	12	12	12	12	12	12	12
Month FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses: ***, **, * indicate the statistically significant difference from zero at the 0.1, 1 and 5 percent levels respectively.

Table 11: Canadian exports and exchange rate

	(a) Dependent variable: ln(energy exports)								
Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ψ	-0.001	-0.003	0.004	0.006	0.005	0.006	-0.002	-0.002	0.005
	[0.004]	[0.003]	[0.005]	[0.005]	[0.004]	[0.005]	[0.005]	[0.005]	[0.008]
Observations	264	264	264	264	264	264	264	264	264
R^2	0.98	0.97	0.97	0.97	0.98	0.97	0.97	0.97	0.97
Lags	12	12	12	12	12	12	12	12	12
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(b) Dependent variable: ln(CAD)								
Horizon (h)	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ψ	0.002	-0.003	-0.004	-0.001	0.002	0.003	0.001	0.002	0.005
	[0.002]	[0.005]	[0.006]	[0.005]	[0.005]	[0.005]	[0.005]	[0.004]	[0.003]
Observations	468	468	468	468	468	468	468	468	468
R^2	0.99	0.98	0.97	0.96	0.96	0.96	0.96	0.96	0.96
Lags	12	12	12	12	12	12	12	12	12
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses: ***, **, * indicate the statistically significant difference from zero at the 0.1, 1 and 5 percent levels respectively.