Are supply curves convex? Implications for state-dependent responses to shocks*

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PRELIMINARY

Abstract

This paper studies whether responses to shocks are state-dependent. To guide our empirical analysis we develop a putty-clay model in which short-run capacity constraints generate a convex supply curve at the industry level. Using a sufficient statistics approach, we estimate the model and find strong support for state-dependent responses to shocks. Industries with low initial capacity utilization rates expand production much more after dollar depreciations or defense spending shocks than industries that produce close to their capacity limit. Further, prices rise after such demand shocks only if the initial level of capacity utilization is high. Our evidence supports the view that supply curves are convex at the industry level and suggests that policies that raise demand are more effective during slumps.

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1 Introduction

An important question for policymakers is whether the effects of fiscal and monetary policy depend on the state of the business cycle. While this question has received significant attention, there is as yet no consensus in the literature. A number of studies find that the fiscal multiplier is larger in recessions (e.g. Auerbach and Gorodnichenko, 2012, 2013a, 2013b), but others argue that such state dependence is small or nonexistent (Ramey and Zubairy, 2014). Studies on monetary policy reflect an even larger degree of disagreement. For instance, Tenreyro and Thwaites (2016) find that monetary policy is less effective in recessions while Santoro et al. (2014) conclude that it is more effective. A unifying theme in these papers is that they estimate state-dependent responses to one particular shock.

In light of its relevance for policymaking this paper revisits this question. In contrast to earlier work, we focus on one specific mechanism—rather than a shock—and ask whether this mechanism is supported by the data. There are a number of advantages of this approach. First, we can use multiple sources of variation to test for the presence of the same mechanism. Further, if present, this mechanism implies that responses to *any* shock are state dependent (although other nonlinearities could offset the identified channel). Due to its salience in the literature, we ask whether the data supports the conjecture that supply curves are convex. Although this question is quite simple, the notorious shortage of good instruments implies that even the slope of supply curves is typically difficult to identify (e.g. Shea, 1993). To obtain sufficient variation for robust and precise estimates we conduct our analysis at the industry level.

Our main finding is that there is surprisingly strong evidence for convex supply curves and state-dependent responses to shocks. Our empirical analysis shows that production responds much more when the initial level of capacity utilization is low. Further, industries with high initial capacity utilization experience price increases when subjected to positive demand shocks while industries with low utilization rates do not. These results hold for two different demand shocks, one based on appropriately purified exchange rate movements and another based on variation in defense spending.

Using confidential Census data, we begin our analysis with a plausibility check of whether capacity is a likely determinant of firms' responsiveness to shocks. We show that a significant and procyclical fraction of plants produces at their self-reported level of full capacity. These plants are presumably slow at adjusting production when subjected to a positive demand shock. Further, a large share of plants produce below capacity, and at times far below. The vast majority of these firms cites insufficient demand as the main reason for producing below capacity. We interpret these facts as evidence for a putty-clay type scale choice that requires plants to choose their maximum capacity prior to production.

Equipped with these facts, we develop a model to guide our empirical analysis. Building on earlier work by Fagnart, Licandro, and Portier (1999), the main assumption is that firms invest into a set of factors that are fixed in the short run and, once chosen, determine the firm's maximum productive capacity. When the demand for a firm's good materializes sufficiently high, production becomes constrained by capacity and unresponsive to shocks. Our framework permits simple aggregation to the industry level, where it generates a convex supply curve.

The additional structure imposed by the model has a number of advantages. First, it allows us to be precise about the relevant measure of the state of the economy that determines the responsiveness to shocks. In our framework the capacity utilization rate—the level of actual production divided by full capacity production—is a sufficient statistic for this state. Since the Federal Reserve estimates and publishes close analogues to the model's capacity utilization rates we do not need to rely on ad-hoc measures that may or may not affect responses to shocks.

Second, the model provides guidance for the empirical analysis by implying a set of estimating equations which contain the relevant control variables. The model also predicts that, conditional on this set of controls, exchange rate fluctuations lead to shifts in demand curves akin to those of government spending shocks. We can therefore trace out the slope and curvature of industry's supply curves using two sources of variation: 1) an appropriately purified effective exchange rate measure and 2) changes in defense spending. Since both shocks require assumptions for consistent estimation, it is critical that our results hold for both shocks.[1] In either case the evidence supports the conclusion that supply curves are convex and responses to shocks state dependent.

Finally, and as noted earlier, the structural approach implies that our findings are relevant for all types of shocks. In the presence of curvature, the elasticities that determine how the economy responds to shocks depend on the state of the economy. We provide information on how to calibrate the convexity of supply curves. Further, our estimates suggest that the degree of state dependence

[1]We draw on findings in the literature on exchange rates, including Campa and Goldberg (2005), Gopinath and Rigobon (2008), and Amiti, Itskhoki, and Konings (2014).

is large. Based on our preferred estimates, production increases by 4.69 percent after a one percent depreciation of the effective exchange rate when the initial capacity utilization rate is at the 10th percentile of the distribution. In contrast, at the 90th percentile of utilization, this elasticity is significantly lower with a value of merely 1.11.

Our paper complements earlier work on state-dependent responses to shocks. These papers include, but are not limited to, Weise (1999), Peersman and Smets (2005), Lo and Piger (2005), Baum, Poplawski-Ribeiro, and Weber (2012), Owyang, Ramey, and Zubairy (2013), Fazzari, Morley, and Panovska (2015), Jordà, Schularick, and Taylor (2017), and those cited above. All of these papers study one particular shock, rather than a mechanism—as we do. Further, we conduct our empirical analysis at the industry level to obtain more statistical power.

Capacity utilization measures how much a firm or plant produces relative to how much it can to produce (capacity). It is important to note that this concept is different from, though related to, *capital utilization* which measures the fraction of time the capital stock operates.[2] A large literature in macroeconomics has studied models in which capital services vary at high frequencies due to a utilization choice (see, e.g. Greenwood, Hercowitz, and Huffman, 1988, Bils and Cho, 1994, Cooley, Hansen, and Prescott, 1995, Burnside and Eichenbaum, 1996, Fagnart, Licandro, and Sneessens, 1997, Gilchrist and Williams, 2000, Hansen and Prescott, 2005).[3] Relative to that literature the nonlinear implications of capacity utilization have received less attention. We find this somewhat surprising given the literature on borrowing constraints—the canonical analogue on the consumer side—is truly vast. Two important exceptions are Michaillat (2014), who develops the idea that slack in the labor market (or a convex labor supply curve) leads to state-dependent fiscal multipliers, and Kuhn and George (2017) who study the quantitative implications of convex supply curves in general equilibrium.[4]

We begin in section 2 with establishing basic facts on capacity utilization at the plant level. In section 3 we develop a simple illustrative model that features such utilization of capacity and use it to motivate our empirical strategy. After discussing the data we present our baseline empirical results in section 4, using exchange rate variation for identification. We extend the empirical analysis to defense spending shocks in section 5. Section 6 concludes.

[2] In the literature this distinction is sometimes blurry.

[3] See also Alvarez-Lois (2004, 2006).

[4] For empirical work on capacity and capital utilization, see Shapiro (1989), Stock and Watson (1999), and Gorodnichenko and Shapiro (2011).

2 Capacity utilization at the plant level

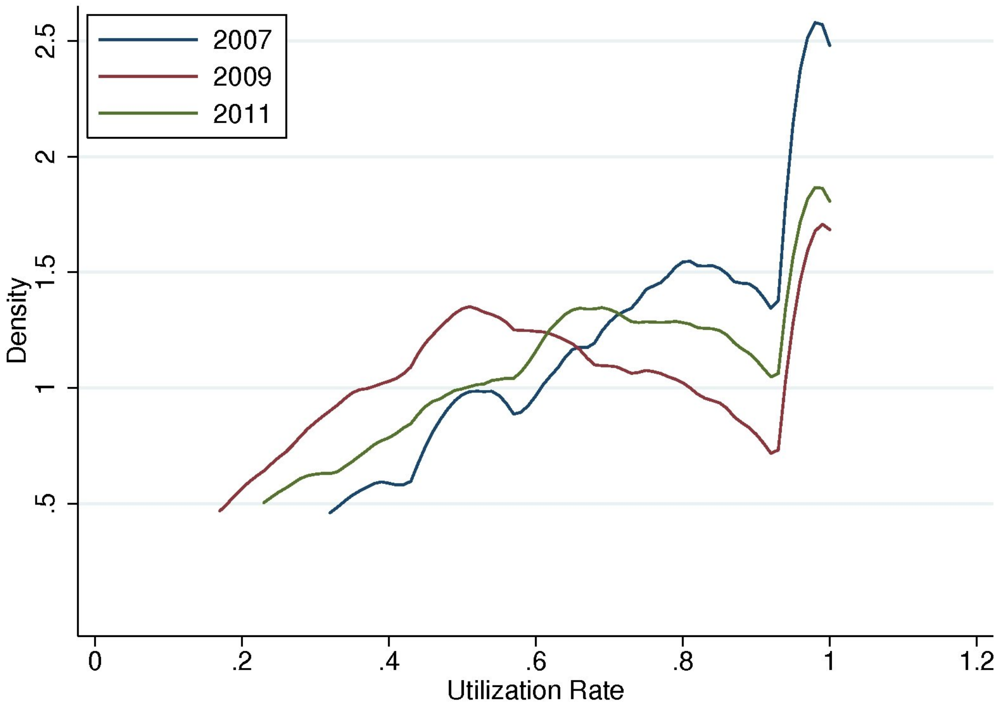
We begin with presenting several basic facts on plants' capacity utilization using microdata from the Quarterly Survey of Plant Capacity Utilization (QSPC). The survey is conducted by the U.S. Census Bureau and funded jointly by the Federal Reserve Board and the Department of Defense. The sample is drawn from all U.S. manufacturing and publishing plants with 5 or more production employees. Among other things, establishments are asked about the market value of their *actual production* and the estimated market value of their *full production capacity*. Respondents are asked to construct this estimate under the following assumptions: 1) only the current functional machinery and equipment is available, 2) normal downtime, 3) labor, materials, and other non-capital inputs are fully available, 4) a realistic and sustainable shift and work schedule, and 5) that the establishment produces the same product mix as its current production.[5] Capacity utilization rates are then obtained by dividing the market value of actual production by the estimate of full capacity production.

Figure 1 plots the density estimates of utilization rates for the years 2007, 2009 and 2011. Utilization rates display substantial cross-sectional variation and three facts emerge from the figure. First, a significant fraction of establishments produces at full capacity. In all three years, a discrete mass of establishments bunches at a utilization rate of unity. Second, an even larger share of plants produces below their reported capacity, at times far below: Utilization rates between 0.2 and 0.5 are not uncommon. Finally, capacity utilization rates and the fraction of firms with utilization rates of unity are highly procyclical. In 2007 a large fraction of plants produced at full capacity and the density displays a mode at around 0.8. By 2009 the distribution has shifted to the left and has a modal point at approximately 0.5. The 2011 density reflects partial recovery relative to 2009 but utilization rates are still below those of 2007.

We next turn to the question why establishments produce at levels below their capacity. Respondents of the QSPC are asked: "If this plant's actual production in the current quarter was less than full production capacity, mark (X) the primary reasons." Possible answers include "Insufficient supply of materials", "Insufficient orders", "Insufficient supply of local labor force/skills", and others. Multiple answers are permitted. It turns out that the vast majority of plants produce

[5] A survey form of the Quarterly Survey of Plant Capacity Utilization is available at `https://bhs.econ.census.gov/bhs/pcu/watermark_form.pdf`.

Figure 1: Densities of plant capacity utilization



Notes: The data are from the QSPC of the U.S. Census Bureau. The figure shows kernel density estimates which are truncated below the 5th and above the 95th percentile due to Census disclosure requirements.

below capacity because they are not able to sell their products. For the time period from 2013q1 to 2017q2 for which public data is available, 79.7 percent of plant managers cite insufficient orders as the main reason for producing below capacity. The second most cited option is chosen by 10.0 percent of respondents (insufficient supply of local labor force/skills).

While neither of these facts is surprising, they are a necessary condition for a connection between capacity and the responsiveness to shocks. Further, these facts pose difficulties to the standard neoclassical production function which assumes a strictly positive marginal product of labor. In contrast, the data appear to support a putty-clay-type view according to which firms first choose their production capacity and subsequently produce either at or below capacity. For a plant that produces at capacity, hiring more workers does not raise output unless it expands capacity as well. In the next section, we use these facts to motivate our choice of a putty-clay type production function.

3 Model

The main objective of this theoretical analysis is to develop a theory that (1) can generate a convex supply curve and (2) will guide our empirical analysis. We begin with a simple illustrative model and subsequently consider generalizations with greater realism.

Our framework features a competitive aggregating firm and monopolistically competitive intermediate goods firms. In order to generate a notion of capacity and utilization we assume a putty-clay-type production function (as in Fagnart, Licandro, and Portier, 1999) which requires firms to choose their maximum scale prior to making the actual production decision. If demand materializes sufficiently high, production will be constrained by capacity.

3.1 Aggregating firm

A competitive aggregating firm uses a unit continuum of varieties, indexed j as inputs into a constant elasticity of substitution (CES) aggregator to produce the industry's composite good,

$$X_t = \left(\int_0^1 v_t(j)^{\frac{1}{\theta}} x_t(j)^{\frac{\theta-1}{\theta}} dj \right)^{\frac{\theta}{\theta-1}}. \tag{1}$$

The weights v in the aggregator are firm-specific and time-varying. In this baseline version we assume for simplicity that they are drawn independently and identically from distribution G with finite third moment and unit mean.

Taking prices as given, the final goods firm maximizes profits subject to the production function (1). This problem yields the factor demand curves

$$x_t(j) = v_t(j) X_t \left(\frac{p_t(j)}{P_t} \right)^{-\theta} \tag{2}$$

for all j, where the industry's price index is given by

$$P_t = \left(\int_0^1 v_t(j) p_t(j)^{1-\theta} dj \right)^{\frac{1}{1-\theta}}. \tag{3}$$

3.2 Intermediate goods producers

Motivated by our analysis in section 2, we depart from standard theory by assuming that a firm's capacity can limit production in the short run. Following Fagnart, Licandro, and Portier (1999), we assume that the firm has to decide ex-ante on the maximum of variable factors, b_t, that it can employ (or process) in the short run. Since variable factors include primarily production workers and intermediate inputs, b_t has a natural interpretation as workstations or processing capacity of intermediates. To maintain clear notation, we drop the index j throughout this section.

We assume that *firm's idiosyncratic production capacity* takes the form

$$q_t = z_t F(k_t, b_t) \tag{4}$$

where z_t is productivity, k_t is capital, and F is constant returns to scale. The firm's actual production x_t is

$$x_t = q_t \frac{l_t}{b_t} = z_t F(\kappa_t, 1)\, l_t \tag{5}$$

where $\kappa_t = \frac{k_t}{b_t}$ and l_t represents the firm's choice of a bundle of factors that are variable in the short run. Production x_t is limited in the short run because the variable factors l_t cannot exceed b_t. Note that the marginal product of l_t, $z_t F(\kappa_t, 1)$, is constant in the short run and determined by z_t and κ_t. Letting w_t denote the price of input bundle l_t, short run marginal costs are

$$mc_t = \frac{w_t}{z_t F(\kappa_t, 1)}. \tag{6}$$

Firms own their capital stock k and maximize the present value of profits. Investment is subject to (possibly nonconvex) adjustment costs $\phi(i, k)$. The firm's Bellman equation is then

$$V(k, b, z, v) = \max_{x,i,l,b'} \left\{ px - wl - p_i i - \phi(i, k) + \frac{1}{1+r} \mathbb{E}\left[V\left(k', b', z', v'\right)\right] \right\}$$

where the maximization is subject to

$$x \leq q \tag{7}$$

$$k' = (1 - \delta)\, k + i \tag{8}$$

and equations (2) to (5). Equation (7) is the capacity constraint and (8) is the standard capital accumulation equation. In this simple version of the model, we assume that productivity z only has an aggregate (i.e. economy wide) and an industry-specific component, but no firm-specific component.

If the firm operates below its capacity limit, it sets prices at a constant markup over marginal costs. Once it hits its capacity limit, however, it begins to raise the markup so as to equate the quantity demanded to its production capacity. Formally,

$$p = \frac{\theta}{\theta - 1} (mc + \psi), \qquad \psi = 0 \quad \text{whenever} \quad x < q,$$

where ψ is the multiplier on the capacity constraint (7). In this baseline version of the model rising markups are the key channel that generates the convex supply curve. Below we discuss a number of alternative mechanisms that lead to such convexity. These include rationing (in the presence of sticky prices) and kinks in the cost function (for instance due to a shift premium). Notice that only the firm's production and price setting decision are relevant for our purposes, so we do not discuss here the firm's investment decision or its choice of b'.

Since the only source of heterogeneity is the idiosyncratic demand shock v, there exist a threshold variety $\bar{v}$ above which a firm hits the capacity constraint. A lower value of $\bar{v}$ thus indicates that more firms are capacity constrained. It turns out that $\bar{v}$ plays a critical role for characterizing the degree to which the industry uses its productive capacity. For instance, it is possible to write the industry's output as

$$X(q_t, \bar{v}_t) = q_t \left((\bar{v}_t)^{-\frac{\theta-1}{\theta}} \int_0^{\bar{v}_t} v dG(v) + \int_{\bar{v}_t}^{\infty} (v)^{\frac{1}{\theta}} dG(v) \right)^{\frac{\theta}{\theta-1}},$$

that is, the industry's output is only a function of the common idiosyncratic plant capacity q_t, and the threshold variety $\bar{v}$.

3.3 Capacity and utilization

We define the *industry's capacity* as the hypothetical level of output that would be attainable if every intermediate firm produced at full capacity, that is

$$Q_t := \lim_{\bar{v}_t \to 0} X(q_t, \bar{v}_t).$$

Further, we define the industry's utilization rate as the ratio of actual production to full capacity production,

$$u_t := \frac{X(q_t, \bar{v}_t)}{Q_t}. \tag{9}$$

This definition has several attractive properties. First, it is constructed very similar to its empirical counterpart. As we will discuss below, the Federal Reserve constructs its utilization measures by dividing an index of industrial production by its estimate of capacity. Further, the utilization rate u_t can be expressed as an (appropriately constructed) average of firms' idiosyncratic utilization rates $u_t(j)$ which are constructed, as in the Quarterly Survey of Plant Capacity Utilization, by dividing the market value of actual production by the market value of full capacity production $u_t(j) := \frac{x(j)}{q_t} = \frac{p_t x_t(j)}{p_t q_t}$.

Lemma 1. *The utilization rate as defined in (9) has the following properties:*

1. $u_t \in [0, 1]$ *is only a function of* $\bar{v}_t$*:* $u_t = u(\bar{v}_t)$
2. $\lim_{\bar{v}\to 0} u(\bar{v}) = 1$*,* $\lim_{\bar{v}\to\infty} u(\bar{v}) = 0$
3. $u' < 0$
4. *The sign of* u'' *is ambiguous*

The lemma highlights that the industry's utilization rate is only a function of the threshold value $\bar{v}_t$ above which firms produce at full capacity. The utilization rate approaches zero if no firm produces at full capacity and it tends to one if all firms become capacity constrained. Further, u is decreasing everywhere, and thus u is invertible and we can write $\bar{v}_t = \bar{v}(u_t)$. We will make extensive use of this property, both for the remainder of the theoretical analysis and when taking the model to the data.

3.4 The supply curve

One immediate application of the invertibility of u is that the industry's price index (3) can be written as

$$\ln P_t = \Omega(u_t) + \ln(mc_t), \tag{10}$$

where Ω is only a function of the industry's utilization rate. A key insight here is that the supply curve is not a function of output alone, but of utilization, or equivalently of output relative to capacity. If equation (10) is the true model, empirical approaches that disregard the dependence on capacity will suffer from omitted variable bias. In our empirical application below we will show that capacity explains a significant fraction of the variation in prices and output. Further, in some cases excluding capacity from the specification changes other coefficient estimates in quantitatively important ways.

Proposition 1. Ω *has the following properties:*

1. $\Omega'(u) \geq 0$
2. $\lim_{u\to 0} \Omega(u) = \ln \frac{\theta}{\theta-1}$, $\lim_{u\to 1} \Omega(u) = \infty$
3. $\lim_{u\to 0} \Omega'(u) = 0$, $\lim_{u\to 1} \Omega'(u) = \infty$
4. *Without further restrictions on* G*, the sign of* $\Omega''(u)$ *is generally ambiguous.*

Because Ω is increasing in utilization everywhere, the industry's supply curve (10) is upward-sloping. As utilization rises more suppliers become capacity constrained and those that are constrained respond by raising their markups. As the utilization rate approaches one, all suppliers become constrained and Ω and its derivative tend to infinity. Conversely, when the utilization rate tends to zero, fewer and fewer suppliers are capacity constrained. As a result Ω tends to $\ln \frac{\theta}{\theta-1}$ and its derivative to zero. While $\Omega(u)$ is convex everywhere for many choices of G, it is possible to construct examples in which it is locally concave. Thus, whether Ω is convex in the relevant range of utilization remains an empirical question which we will address below.

We briefly turn to a measurement problem that affects estimation and inference. Identifying the slope and curvature of Ω typically requires controlling for marginal costs, which are not observed. Instead, a commonly taken route is to control for unit costs which are observed. Unfortunately, in our framework marginal costs and unit costs differ. Further, the wedge between them is a function of utilization which can lead to biased estimates of Ω' and Ω''.

More specifically, and letting $w_t L_t$ the industries' total expenditure on bundle l_t, marginal costs can be expressed as $\ln mc_t = \ln \frac{w_t L_t}{X_t} + \Psi(u_t)$, where Ψ is only a function of u. Hence, the industry's supply curve (10) becomes

$$\ln P_t = \Omega(u_t) + \Psi(u_t) + \ln \frac{w_t L_t}{X_t}. \qquad (11)$$

Thus, variation in u does not identify Ω', but $\Omega' + \Psi'$ and a similar argument applies to Ω''. The structural approach we take allows us to sign these biases.

Proposition 2. $\Psi \leq 0$, $\Psi' \leq 0$, $\Psi'' \leq 0$.

Hence, empirical strategies that aim to estimate Ω' and Ω'' based on equation (11), exhibit a downward bias (for both the slope and the curvature of Ω). It is thus possible that supply curves are upward-sloping and convex, but the researcher finds no evidence supporting this, not even in large samples. Naturally, this raises the bar of for measuring state dependent responses to shocks in the data.

3.5 Equilibrium

We now close the model, assuming that the assembling firm of industry i sells its output to N countries which have CES demand functions

$$X_{i,n,t} = \omega_{i,n,t} X_{n,t} \left[\frac{P^*_{i,n,t}}{\mathcal{P}^*_{n,t}} \right]^{-\sigma}. \tag{12}$$

Here, $P^*_{i,n,t}$ is the price of the good in local currency (as indicated by the asterisk), $X_{n,t}$ is the country's GDP, and $\mathcal{P}^*_{n,t}$ the associated price index. Each country's demand is subject to an industry-specific demand shock $\omega_{i,n,t}$. Let $\mathcal{E}_{n,t}$ be the exchange rate in US dollars per unit of foreign currency. Then the dollar-denominated price is

$$P_{i,n,t} = \mathcal{E}_{n,t} P^*_{i,n,t}, \tag{13}$$

and since there is no pricing to market $P_{i,n,t} = P_{i,t}$. Letting $G_{i,t}$ denote government purchases of the good of industry i, market clearing requires that

$$X_{i,t} = G_{i,t} + \sum_n X_{i,n,t}. \tag{14}$$

An equilibrium in industry i satisfies equations (11) through (14).

We next solve for the reduced form after log-linearizing around the equilibrium in $t-1$. Before showing the equations, it is useful to define and discuss the following objects. First, the change of industry i's effective nominal exchange rate is

$$\Delta e_{i,t} := \sum_n s_{i,n,t-1} \Delta \ln \mathcal{E}_{n,t}. \tag{15}$$

In this expression $s_{i,n,t-1}$ denotes the $t-1$ sales share of industry i to country n. Notice that $\Delta e_{i,t}$ varies by industry because existing trade linkages differentially expose industries to fluctuations of a common set of currencies. The effective exchange rate change as defined in (15) takes into account that some industries sell more of their goods abroad than others. Industries that sell most of their goods domestically have a U.S. sales share near one. This share is then multiplied by $\Delta \ln \mathcal{E}_{n,t}$ which is zero for the U.S. A positive value of $\Delta e_{i,t}$ reflects a depreciation of the U.S. dollar relative to the relevant basket of foreign currencies. From the viewpoint of a firm or industry that sets prices in dollars such a depreciation leads to an increase in demand. Below we will use the empirical counterpart of this measure as a demand shock to test the state dependence hypothesis.

We further define

$$\Delta \xi_{i,t} := \sum_n s_{i,n,t-1} \Delta \ln X_{n,t} \quad \text{and} \quad \Delta \pi_{i,t} := \sum_n s_{i,n,t-1} \Delta \ln P^*_{n,t}, \tag{16}$$

which reflect changes in demand due to changes in a destination's market size and prices, respectively. Both measures rely on the same model-based weighting scheme as the exchange rate measure (15) and thus vary by industry. Finally, let $\Delta g_{i,t} := \left(G_{i,t} - G_{i,t-1}\right) / X_{i,t-1}$, that is $\Delta g_{i,t}$ is the change in government spending as a fraction of the industry's level of output at $t-1$.

Proposition 3. *The reduced form, linearized around the equilibrium in $t-1$, is*

$$\begin{aligned} \Delta \ln X_{i,t} &= \beta_e\left(u_{i,t-1}\right) \Delta e_{i,t} + \beta_\xi\left(u_{i,t-1}\right) \Delta \xi_{i,t} + \beta_\pi\left(u_{i,t-1}\right) \Delta \pi_{i,t} + \beta_g\left(u_{i,t-1}\right) \Delta g_{i,t} \\ &\quad + \beta_Q\left(u_{i,t-1}\right) \Delta \ln Q_{i,t} + \beta_{uc}\left(u_{i,t-1}\right) \Delta \ln \frac{w_{i,t} L_{i,t}}{X_{i,t}} + \omega^X_{i,t}, \end{aligned} \tag{17}$$

$$\begin{aligned} \Delta \ln P_{i,t} &= \gamma_e\left(u_{i,t-1}\right) \Delta e_{i,t} + \gamma_\xi\left(u_{i,t-1}\right) \Delta \xi_{i,t} + \gamma_\pi\left(u_{i,t-1}\right) \Delta \pi_{i,t} + \gamma_g\left(u_{i,t-1}\right) \Delta g_{i,t} \\ &\quad + \gamma_Q\left(u_{i,t-1}\right) \Delta \ln Q_{i,t} + \gamma_{uc}\left(u_{i,t-1}\right) \Delta \ln \frac{w_{i,t} L_{i,t}}{X_{i,t}} + \omega^P_{i,t}. \end{aligned} \tag{18}$$

All coefficients are functions of the utilization rate (and only of the utilization rate) and $\beta_e > 0$,

$\beta_\xi > 0$, $\beta_\pi > 0$, $\beta_g > 0$, $\beta_{uc} < 0$, $\beta_Q > 0$, $\gamma_e > 0$, $\gamma_\xi > 0$, $\gamma_\pi > 0$, $\gamma_g > 0$, $\gamma_{uc} > 0$, $\gamma_Q < 0$. The error terms are given by

$$\omega_{i,t}^X = \omega^X (u_{i,t-1}) \sum_n s_{i,n,t-1} \Delta \ln \omega_{i,n,t} \tag{19}$$

$$\omega_{i,t}^P = \omega^P (u_{i,t-1}) \sum_n s_{i,n,t-1} \Delta \ln \omega_{i,n,t} \tag{20}$$

where ω^X and ω^P are only functions of $u_{i,t-1}$.

4 Empirical analysis: exchange rate shocks

4.1 Data

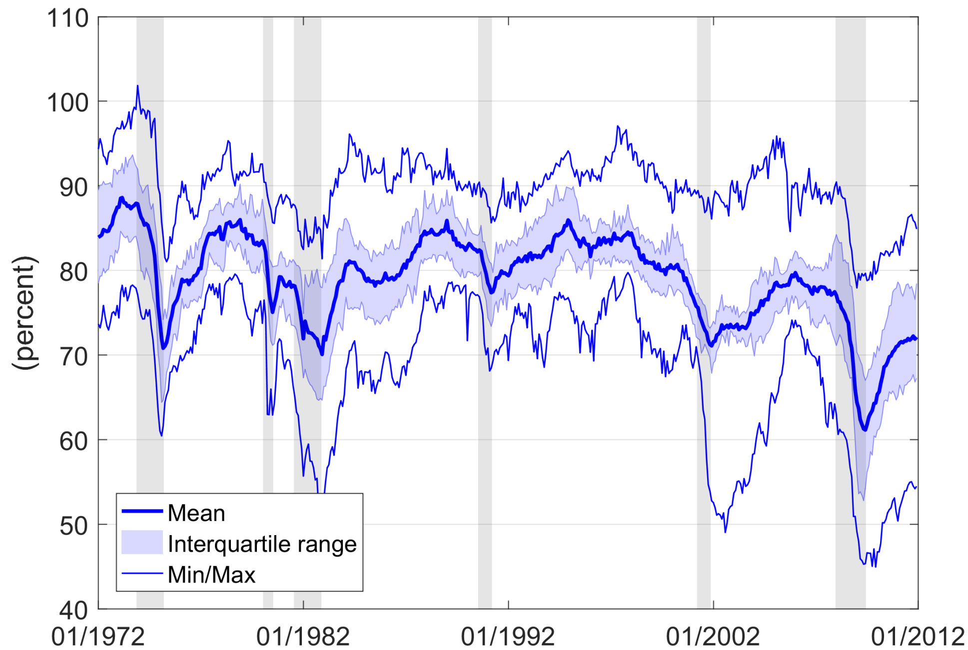
Our preferred measures of capacity and utilization are constructed and published by the Federal Reserve Board (FRB). To obtain series for utilization, the FRB first constructs indexes of industrial production and capacity. The industrial production series are indexes of real gross output. The FRB's capacity indexes aim to capture the *sustainable maximum level of output*, that is, "the greatest level of output a plant [or industry] can maintain within the framework of a realistic work schedule after factoring in normal downtime and assuming sufficient availability of inputs to operate the capital in place".[6] The annual FRB measure of capacity is primarily based on establishment-level utilization rates from the Survey of Plant Capacity (prior to 2007), the Quarterly Survey of Plant Capacity (from 2007 onwards), and measures of capital from the Annual Survey of Manufacturers.[7] As in our model, utilization is then constructed by dividing industrial production by capacity (see equation 9).

Figure 2 illustrates the capacity utilization rates of the 21 3-digit NAICS manufacturing industries in our sample. As is clear from the figure, utilization rates display significant heterogeneity both in the cross-section and over time. Capacity utilization is strongly procyclical and experiences a mild downward trend towards the end of the sample, presumably reflecting the well-documented shrinkage of the U.S. manufacturing sector. An additional salient feature which we document in

[6]See `https://www.federalreserve.gov/releases/g17/Meth/MethCap.htm`. A consequence of this definition is that utilization can exceed unity for short periods of time. In practice, this rarely happens. In our 3-digt NAICS sample from 1972 to 2011 only one industry (Primary Metal Manufacturing, NAICS 331) exceeded a utilization rate of 100 and only for two months (December of 1973 and January of 1974).

[7]For further details on the data sources and methodology underlying of the capacity indexes, see Gilbert, Morin, and Raddock (2000) and `https://www.federalreserve.gov/releases/g17/About.htm`.

Figure 2: Capacity utilization at the industry level



Notes: Federal reserve Board. The figure plots the mean, minimum, maximum and interquartile range of the capacity utilization series constructed using the FRB capacity utilization data and industrial production. Shaded areas represent NBER recessions.

Appendix table (C1) is that average utilization rates differ across industries. Since it is not clear whether these differences reflect measurement or industry-specific capacity choices we subtract from all utilization series their industry-specific means. We note, however, that this demeaning does not drive our results.

We take data on prices, sales, and input costs from the NBER CES Manufacturing Industry Database. These data are constructed mainly from sources of the U.S. Census Bureau, the Bureau of Economic Analysis (BEA), and the Bureau of Labor Statistics (BLS) and provide a detailed picture of the U.S. manufacturing sector.[8] To obtain our measure of unit costs, wL/X we sum production worker wages, costs of materials, and expenditures on energy and then divide by real gross output.

We calculate the sales shares $s_{i,n,t}$ by combining the industry sales series from the NBER CES

[8]For a detailed description of this database, see Bartelsman and Gray (1996) and Randy Becker and Marvakov (2016).

Manufacturing Industry Database with the export data available from Peter Schott's website.[9] When constructing $\Delta e_{i,t}$, $\Delta\xi_{i,t}$, and $\Delta\pi_{i,t}$ as described in (15) and (16), we limit ourselves to countries that joined the OECD prior to year 2000, but note that this choice does not drive our results. The data on exchange rates, real domestic absorption (i.e. consumption plus investment), and the associated price level are from the Penn World Tables. Our sample is annual, includes 21 3-digit NAICS manufacturing industries, and ranges from 1972 to 2011.

4.2 Empirical specification and identification

To estimate equations (17) and (18), we approximate the coefficients linearly around the industry-specific mean, so that, for instance, $\beta_e(u_{i,t-1}) = \beta_e + \beta_{eu}(u_{i,t-1} - \bar{u}_i)$. To preserve clarity and with abuse of notation, we will continue to denote the demeaned utilization measure by $u_{i,t-1}$. Further, we add $u_{i,t-1}$ to the specification in order to obtain the conventional interpretation of the interaction terms, and set government spending to zero. This yields our baseline estimating equations:

$$\begin{aligned}\Delta \ln X_{i,t} \quad = \quad & \beta_e \Delta e_{i,t} + \beta_{eu}\Delta e_{i,t} u_{i,t-1} + \beta_\xi \Delta\xi_{i,t} + \beta_{\xi u}\Delta\xi_{i,t} u_{i,t-1} \\ & + \beta_\pi \Delta\pi_{i,t} + \beta_{\pi u}\Delta\pi_{i,t} u_{i,t-1} + \beta_Q \Delta \ln Q_{i,t} + \beta_{Qu}\Delta \ln Q_{i,t} u_{i,t-1} \\ & + \beta_{uc}\Delta \ln \frac{w_{i,t}L_{i,t}}{X_{i,t}} + \beta_{ucu}\Delta \ln \frac{w_{i,t}L_{i,t}}{X_{i,t}} u_{i,t-1} + \beta_u u_{i,t-1} + \omega^X_{i,t},\end{aligned} \tag{21}$$

$$\begin{aligned}\Delta \ln P_{i,t} \quad = \quad & \gamma_e \Delta e_{i,t} + \gamma_{eu}\Delta e_{i,t} u_{i,t-1} + \gamma_\xi \Delta\xi_{i,t} + \gamma_{\xi u}\Delta\xi_{i,t} u_{i,t-1} \\ & + \gamma_\pi \Delta\pi_{i,t} + \gamma_{\pi u}\Delta\pi_{i,t} u_{i,t-1} + \gamma_Q \Delta \ln Q_{i,t} + \gamma_{Qu}\Delta \ln Q_{i,t} u_{i,t-1} \\ & + \gamma_{uc}\Delta \ln \frac{w_{i,t}L_{i,t}}{X_{i,t}} + \gamma_{ucu}\Delta \ln \frac{w_{i,t}L_{i,t}}{X_{i,t}} u_{i,t-1} + \gamma_u u_{i,t-1} + \omega^P_{i,t}.\end{aligned} \tag{22}$$

4.2.1 The exchange rate as a demand shock

The shock we use in this section to identify the curvature of the supply curve is a (purified) change in an industry's effective exchange rate (equation 15). A dollar depreciation relative to the relevant basket of foreign currencies makes U.S.-produced goods cheaper for foreign customers. If firms in

[9] See `http://faculty.som.yale.edu/peterschott/sub_international.htm`. This data is available with SIC industry codes between 1972 and 1997, and with NAICS industry codes thereafter. We use the NBER CES SIC4 to NAICS6 concordance based on sales weights to convert the SIC codes into NAICS equivalents and then aggregate to the 3-digit NAICS level.

the U.S. set prices in U.S. dollars (and 97 percent of U.S. exporters do, see Gopinath and Rigobon (2008)), such depreciations materialize as outward shifts in demand. A one percent depreciation of the effective exchange rate raises demand by the value of the demand elasticity.

As Amiti, Itskhoki, and Konings (2014) emphasize, most exporters also import and hence dollar depreciations raise the cost of intermediates inputs. To prevent this channel from confounding our interpretation of dollar depreciations as demand shocks, we control for unit costs as suggested by the model in all our specification.

Although there is a well-documented disconnect between exchange rate movements and other macroeconomic aggregates, it is important to acknowledge that exchange rates are endogenous variables. To the extent that the shocks driving exchange rate movements are not appropriately controlled for in our model (for instance, through $\Delta\xi_{i,t}$ and $\Delta\pi_{i,t}$), our estimates could be biased. We thus purify the exchange rate movements as follows. Let $\Delta\ln\mathcal{E}_t^{com}$ denote changes in the value of the U.S. dollar that are common to all currencies and $\Delta\ln\mathcal{E}_{n,t}^{spec}$ movements that are specific to the currency of country n. Then it is possible to write

$$\Delta\ln\mathcal{E}_{n,t} = \Delta\ln\mathcal{E}_t^{com} + \Delta\ln\mathcal{E}_{n,t}^{spec}. \tag{23}$$

This decomposition can be implemented by regressing the observed changes in exchange rates on a set of time fixed effects. In our sample, the R^2 of this regression is 28.3 percent, implying that 28.3 percent of changes in the dollar value of foreign currencies are common to all foreign currencies. Since these common changes could be caused by U.S. macro shocks which could also affect the manufacturing industries in our sample through other, non-exchange rate channels, we find it useful to develop a way to control for them.

To do so, denote by $n = 0, 1, ..., N$ the destination countries for manufacturing exports, letting $n = 0$ be the U.S. Since $\Delta\ln\mathcal{E}_{0,t} = 0$ for all t, we can always write $\Delta e_{i,t} = \sum_{n=0}^{N} s_{i,n,t-1}\Delta\ln\mathcal{E}_{n,t} = \sum_{n=1}^{N} s_{i,n,t-1}\Delta\ln\mathcal{E}_{n,t}$. Further, let $\bar{s}_{n,t-1}$ denote the sales share to country n for all of U.S. manufacturing, i.e. the aggregate of all industries in the sample. Then, using decomposition (23), we obtain

$$\Delta e_{i,t} = \Delta\ln\mathcal{E}_t^{com}\sum_{n=1}^{N} s_{i,n,t-1} + \sum_{n=1}^{N}\bar{s}_{n,t-1}\Delta\ln\mathcal{E}_{n,t}^{spec} + \sum_{n=1}^{N}\left(s_{i,n,t-1} - \bar{s}_{n,t-1}\right)\Delta\ln\mathcal{E}_{n,t}^{spec}. \tag{24}$$

The first term in equation (24) represents dollar movements that are common to all foreign currencies. Since industries are differentially exposed to the common component of exchange rate movements, $\Delta \ln \mathcal{E}_t^{com}$ is multiplied by the foreign sales shares $\sum_{n=1}^{N} s_{i,n,t-1} = 1 - s_{i,0,t-1}$. If global or U.S. aggregate shocks cause dollar movements relative to all foreign currencies and this variation is a concern for identification, these shocks can be perfectly controlled for by including an interaction of a set of time fixed effects with the industries' foreign sales shares in the regression. We will do so below.

The second term in equation (24) represents country-specific exchange rate movements weighted up into an effective exchange rate using the sales shares for all of U.S. manufacturing. This term does not vary by industry and can therefore be controlled for with time fixed effects.

The third and final term in equation (24) captures the remainder of the variation of the industries' effective exchange rates and constitutes the cleanest measure of our demand shock (holding unit costs constant). It weights destination-specific exchange rate movements with the deviations of sales shares from the manufacturing average. Possible confounders are now limited to shocks that 1) move destination-specific exchange rates (and not the dollar relative to all currencies), 2) differentially affect the industries in the sample in a way that is correlated with these industries' export patterns, 3) through a channel that is not the exchange rate itself, and 4) in a way that is not controlled for through $\Delta\xi_{i,t}$ and $\Delta\pi_{i,t}$ (or other controls).

It is not impossible to come up with candidates that still pose a problem for identification. Foreign monetary and financial shocks are two examples and credibly controlling for these is difficult. While the bias is likely small, we use an alternative demand shock to verify that our results are not driven by these confounding factors. In the next section we will use federal defense spending to identify the curvature of the supply shock. The economic conclusions are similar, although the estimates are less precise.

4.2.2 Additional notes on identification

We briefly discuss three additional identification concerns. First, it is likely that the regression errors are correlated with utilization. Our structural approach alleviates this concern relative to other studies because it suggests a number of controls, including the change in capacity, $\Delta \ln Q_{i,t}$.[10]

[10] Since firms and industries with high utilization rates expand capacity, $\Delta \ln Q_{i,t}$ has an unconditional correlation with $u_{i,t-1}$ of 39%.

Yet, adding such controls does not necessarily remedy the problem fully because unobservables such as the demand shocks $\omega_{i,n,t}$ in the structural errors $\omega_{i,t}^{X}$ and $\omega_{i,t}^{P}$ could be correlated with $u_{i,t-1}$.[11] To understand this concern we ran a number of Monte-Carlo experiments and found that while the coefficients on utilization were generally biased, the coefficient on the interaction was not.

Second, and as discussed in section 3.4, variation in the interaction term $\Delta e_{i,t} u_{i,t-1}$ does not exclusively identify the curvature of the supply curve Ω'', but also the curvature in the wedge between marginal costs and unit costs. Proposition (2) implied that we will always understate the convexity of the supply curve, which places us on the conservative side.

Third and finally, our model is likely misspecified. Features such as price stickiness and more general specifications of heterogeneity are important features of the real world. We will consider generalizations of the model and the associated robustness exercises below.

4.3 Results

We begin with estimating of linear versions of (21) and (22). The estimates for $\Delta \ln X_{i,t}$ as the dependent variable are shown in table 1. In the absence of our model's guidance the canonical starting point is to omit capacity on the right hand side. We report the associated estimates as specification (1). All variables have the expected signs, but the coefficient on the effective exchange rate is not significant. Once we add capacity to the model (specification 2), the exchange rate response increases and becomes statistically significant at the 1 percent level. The observation that all other coefficient estimates also change (in particular the coefficient on $\Delta \pi_{i,t}$) suggests that controlling for capacity may be important. When interpreted through the lens of the model, controlling for capacity captures all relevant dynamic margins for production and price setting. While this interpretation is presumably too strong, it is likely that changes in capacity do help control for industries' low frequency dynamics or anticipation effects. Note that specification (2), which is quite parsimonious with only 5 regressors, explains about 50 percent of the variation in the data.

We next sequentially add in fixed effects to see whether doing so affects the exchange rate response. Unsurprisingly, adding industry fixed effects to account for differential growth rates changes little (specification 3). The exchange rate response shrinks somewhat when time fixed effects are

[11] This would be the case, for instance, if the unobserved demand shocks in changes, $\Delta \ln \omega_{i,n,t}$, were autocorrelated (see equations 19 and 20).

Table 1: Linear model for dependent variable $\Delta \ln X_{i,t}$

Specification	(1)	(2)	(3)	(4)	(5)
$\Delta e_{i,t}$	2.14	3.51***	3.60***	2.69**	2.56*
	(1.30)	(1.09)	(1.07)	(1.08)	(1.31)
$\Delta \xi_{i,t}$	1.81***	1.57***	1.57***	-1.29	4.94
	(0.24)	(0.20)	(0.20)	(2.04)	(4.16)
$\Delta \pi_{i,t}$	0.42**	0.05	0.09	-3.78	-3.48
	(0.20)	(0.16)	(0.18)	(2.27)	(3.16)
$\Delta \ln Q_{i,t}$		0.71***	0.71***	0.79***	0.76***
		(0.07)	(0.09)	(0.08)	(0.08)
$\Delta \ln \frac{w_{i,t} L_{i,t}}{X_{i,t}}$	-0.18**	-0.10	-0.13**	-0.20**	-0.20**
	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)
Observations	819	819	819	819	819
R-squared	0.355	0.498	0.509	0.641	0.677
Industry FE	no	no	yes	yes	yes
Time FE	no	no	no	yes	yes
Time FE $\times (1 - s_{i,0,t-1})$	no	no	no	no	yes

Notes: Driscoll-Kraay standard errors in parentheses. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.

also included (specification 4), but the qualitative interpretation remains the same. In specification (5) we additionally add a set of time fixed effects interacted with industries' foreign sales share to purify the exchange rate shock from potential confounders that lead to dollar movements against all foreign currencies. The fact that the coefficient estimate on $\Delta e_{i,t}$ barely changes increases our confidence that $\Delta e_{i,t}$ accurately captures changes in foreign demand after dollar depreciations rather than an omitted variable.

Table 2 presents an analogous set of estimates for $\Delta \ln P_{i,t}$ as the dependent variable. The most striking feature in this table is the importance of unit costs to explain prices. A regression of the percent change in prices on the percent change in unit costs (not reported) yields an R-squared of 0.900, just marginally below the R-squared of specification (1) in table 2. All other variables, including the exchange rate variable $\Delta e_{i,t}$, are relatively unimportant and not generally significant, independent of whether we control for capacity (specification 2) and whether we add additional fixed effects (specifications 3 to 5). The fact that even well identified shocks have little effect on prices is not uncommon in the literature (see, e.g. House and Shapiro, 2008 and Shapiro, 1989).

We present the first set of state-dependent specifications with $\Delta \ln X_{i,t}$ as the dependent variable in table 3. Specification (1) shows the estimates of equation (21). Both the main effect of

Table 2: Linear model for dependent variable $\Delta \ln P_{i,t}$

Specification	(1)	(2)	(3)	(4)	(5)
$\Delta e_{i,t}$	-0.16	-0.19	-0.19	-0.22	0.30
	(0.29)	(0.26)	(0.25)	(0.29)	(0.74)
$\Delta \xi_{i,t}$	-0.02	-0.01	-0.02	0.58	-4.02*
	(0.04)	(0.04)	(0.03)	(0.66)	(2.22)
$\Delta \pi_{i,t}$	0.12***	0.13***	0.14***	0.15	-1.19
	(0.03)	(0.03)	(0.04)	(0.63)	(1.08)
$\Delta \ln Q_{i,t}$		-0.02	0.00	0.00	0.02
		(0.03)	(0.04)	(0.04)	(0.03)
$\Delta \ln \frac{w_{i,t} L_{i,t}}{X_{i,t}}$	0.83***	0.83***	0.82***	0.87***	0.86***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	819	819	819	819	819
R-squared	0.902	0.902	0.904	0.918	0.925
Industry FE	no	no	yes	yes	yes
Time FE	no	no	no	yes	yes
Time FE $\times (1 - s_{i,0,t-1})$	no	no	no	no	yes

Notes: Driscoll-Kraay standard errors in parentheses. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.

the effective exchange rate as well as the interaction term with lagged utilization are statistically significant. The coefficient on the interaction term is also economically very large. At the 10th percentile of the demeaned utilization rate ($u_{i,t-1} = -0.085$), a one percent depreciation of the dollar leads to a $4.69\,(= 2.79 + (-22.30) \times (-0.085))$ percent increase in the industry's quantity produced. In contrast, the same elasticity is only $1.11\,(= 2.79 + (-22.30) \times 0.075)$ at the 90th percentile ($u_{i,t-1} = 0.075$).

Specifications (2) to (4) of table 3 sequentially add industry fixed effects, time fixed effects, and the interaction of time fixed effects with the industries' foreign sales shares. In all cases is the coefficient on the interaction term of the exchange rate with utilization large and significant. In fact, it becomes larger as more fixed effects are added to the regression. Finally, specification (5) includes as additional controls squared terms of $u_{i,t}, \Delta e_{i,t}, \Delta \xi_{i,t}, \Delta \pi_{i,t}, \Delta \ln Q_{i,t}, \Delta \ln \frac{w_{i,t} L_{i,t}}{X_{i,t}}$ as well as all possible interactions of $\Delta e_{i,t}, \Delta \xi_{i,t}, \Delta \pi_{i,t}, \Delta \ln Q_{i,t}, \Delta \ln \frac{w_{i,t} L_{i,t}}{X_{i,t}}$. Again, the coefficient of interest is essentially unchanged.

Table 4 presents an analogous set of estimates for $\Delta \ln P_{i,t}$ as the dependent variable. As in the linear specifications of table 2 the main effect of the effective exchange rate is not generally significant. However, the coefficient on the interaction term with the utilization rate is positive and

Table 3: State-dependent model for dependent variable $\Delta \ln X_{i,t}$

	(1)	(2)	(3)	(4)	(5)
$\Delta e_{i,t}$	2.79***	2.85***	1.27	2.02**	1.87
	(0.75)	(0.72)	(0.90)	(0.85)	(2.07)
$\Delta e_{i,t} \times u_{i,t-1}$	-22.30**	-25.44***	-24.40***	-31.35***	-30.00***
	(9.43)	(7.88)	(7.38)	(6.34)	(7.19)
$\Delta \xi_{i,t}$	1.43***	1.39***	0.52	2.05	-12.46
	(0.19)	(0.19)	(2.57)	(5.29)	(19.39)
$\Delta \xi_{i,t} \times u_{i,t-1}$	-2.27	-2.43	-2.08	-1.72	-1.29
	(1.39)	(1.45)	(1.78)	(1.20)	(1.23)
$\Delta \pi_{i,t}$	0.30	0.32	-5.49**	-6.29*	-20.64
	(0.18)	(0.20)	(2.02)	(3.39)	(14.63)
$\Delta \pi_{i,t} \times u_{i,t-1}$	-4.52**	-3.72	-3.62	-4.51	-2.98
	(2.16)	(2.34)	(3.25)	(3.15)	(2.66)
$\Delta \ln Q_{i,t}$	0.81***	0.98***	0.94***	0.92***	0.76***
	(0.06)	(0.13)	(0.13)	(0.12)	(0.15)
$\Delta \ln Q_{i,t} \times u_{i,t-1}$	-0.58	-0.56	-0.52	0.46	0.40
	(0.73)	(0.91)	(0.78)	(0.82)	(0.94)
$\Delta \ln \frac{w_{i,t} L_{i,t}}{X_{i,t}}$	-0.06	-0.10	-0.15*	-0.15*	-0.09
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)
$\Delta \ln \frac{w_{i,t} L_{i,t}}{X_{i,t}} \times u_{i,t-1}$	-0.12	-0.27	0.09	0.67	-0.36
	(1.04)	(0.90)	(0.74)	(0.73)	(0.59)
$u_{i,t-1}$	-0.04	-0.09	-0.16	-0.18**	-0.23**
	(0.09)	(0.08)	(0.10)	(0.09)	(0.08)
Observations	819	819	819	819	819
R-squared	0.554	0.569	0.679	0.714	0.735
Industry FE	no	yes	yes	yes	yes
Time FE	no	no	yes	yes	yes
Time FE $\times (1 - s_{i,0,t-1})$	no	no	no	yes	yes
Higher order controls*	no	no	no	no	yes

Notes: Driscoll-Kraay standard errors in parentheses. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.

significant, consistent with the predictions of a convex supply curve. Further, this result is robust to including industry fixed effects, time fixed effects, the interaction of time fixed effects with the industries' foreign sales shares, and the same set of interactions and squares as discussed above. Economically, the effect is fairly small. Taking the estimates from specification (4), prices rise by $0.68\,(= 0.25 + 5.66 \times 0.075)$ in response to a one percent dollar depreciation relative to the relevant set of foreign currencies when the industry is at the 90th percentile of utilization.[12]

[12]Notice that since our effective exchange rate measure $\Delta e_{i,t}$ places a large weight on the domestic sales share, its standard deviation is small (approximately 0.5 percent). A one percent shock to the effective exchange rate is therefore a very large shock.

Table 4: State-dependent model for dependent variable $\Delta \ln P_{i,t}$

	(1)	(2)	(3)	(4)	(5)
$\Delta e_{i,t}$	-0.12	-0.13	-0.13	0.25	-1.69*
	(0.24)	(0.23)	(0.21)	(0.74)	(0.93)
$\Delta e_{i,t} \times u_{i,t-1}$	4.89**	4.53**	5.99***	5.66***	5.10**
	(1.74)	(1.78)	(1.97)	(1.66)	(1.93)
$\Delta \xi_{i,t}$	0.03	0.03	0.54	-3.48*	-6.35
	(0.05)	(0.05)	(0.58)	(1.85)	(4.68)
$\Delta \xi_{i,t} \times u_{i,t-1}$	1.01***	1.03***	0.73*	0.62*	0.29
	(0.30)	(0.31)	(0.37)	(0.35)	(0.45)
$\Delta \pi_{i,t}$	0.09**	0.09**	0.26	-1.45	-2.04
	(0.04)	(0.04)	(0.61)	(1.14)	(2.33)
$\Delta \pi_{i,t} \times u_{i,t-1}$	0.74	0.87	0.58	0.57	0.28
	(0.79)	(0.70)	(0.86)	(0.81)	(0.89)
$\Delta \ln Q_{i,t}$	-0.01	0.00	0.00	0.02	0.01
	(0.02)	(0.03)	(0.03)	(0.03)	(0.06)
$\Delta \ln Q_{i,t} \times u_{i,t-1}$	-0.47	-0.39	-0.47	-0.45	-0.65
	(0.33)	(0.31)	(0.31)	(0.29)	(0.52)
$\Delta \ln \frac{w_{i,t} L_{i,t}}{X_{i,t}}$	0.83***	0.83***	0.87***	0.87***	0.82***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
$\Delta \ln \frac{w_{i,t} L_{i,t}}{X_{i,t}} \times u_{i,t-1}$	0.46	0.44	0.55	0.45	0.45
	(0.33)	(0.34)	(0.37)	(0.31)	(0.38)
$u_{i,t-1}$	-0.06*	-0.07**	-0.04	-0.04	-0.01
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Observations	819	819	819	819	819
R-squared	0.906	0.908	0.921	0.927	0.932
Industry FE	no	yes	yes	yes	yes
Time FE	no	no	yes	yes	yes
Time FE $\times (1 - s_{i,0,t-1})$	no	no	no	yes	yes
Higher order controls*	no	no	no	no	yes

Notes: Driscoll-Kraay standard errors in parentheses. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.

5 Empirical analysis: government spending shocks

In this section we expand the empirical analysis to government spending shocks to ensure that our results are robust. Many of the details are deferred to the appendix.

5.1 Data

Defense spending series at the industry level are constructed from the military prime contract files and USAspending.gov. The military prime contract files include information on all military prime contracts with values above the minimum threshold of \$10,000 up to 1983 and \$25,000 thereafter.

They can be downloaded for the period from 1966 to 2003 from the U.S. National Archives. We complement this data source with data from USAspending.gov, a government website dedicated to promoting transparency of federal spending. The data from USAspending.gov is available from 2000 onwards. A comparison of the two data sources for the overlapping years from 2000 to 2003 reveals only negligible differences. To assign defense spending to NAICS 3-digit industries, we construct several concordances which we discuss in Appendix X. The remaining data for the analysis are as described in the previous section.

5.2 Empirical specification and identification

We estimate Jordà (2005) local projections of the form

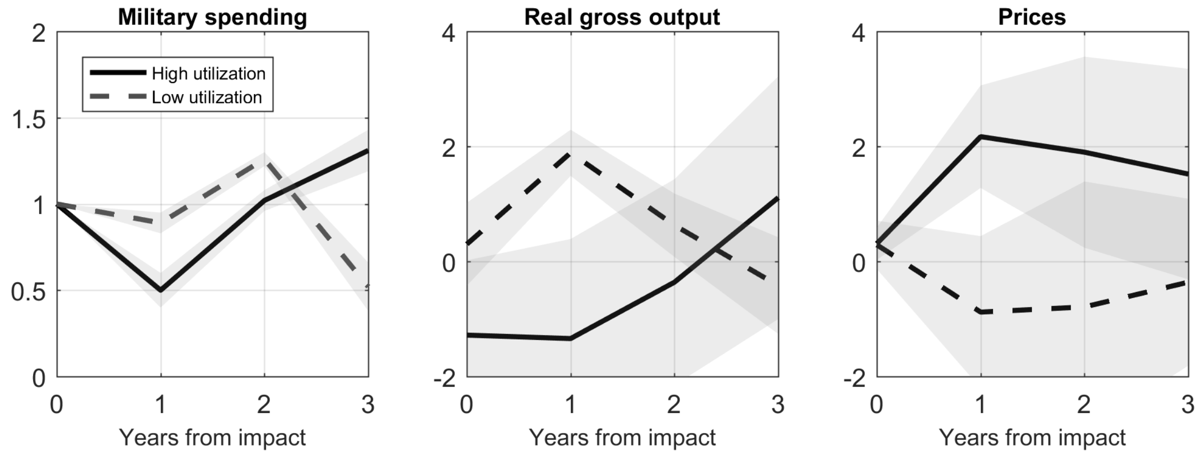
$$\begin{aligned}\frac{X_{i,t+h}-X_{i,t-1}}{X_{i,t-1}} &= \alpha_h^L\left(1-F_{i,t-1}\right)\Delta g_{i,t}+\alpha_h^H F_{i,t-1}\Delta g_{i,t} \\ &\quad +\delta_h Z_{i,t}+\mu_{i,h}+\zeta_{t,h}+\left(1-s_{i,0,t-1}\right)\chi_{t,h}+\varepsilon_{i,t+h}, \qquad (25)\end{aligned}$$

where $F_{i,t}=\frac{\exp(\gamma\cdot u_{i,t})}{1+\exp(\gamma\cdot u_{i,t})}$ and $u_{i,t}$ is the *demeaned* utilization rate. We set γ to 25 which makes this inverse-logit transformation essentially identical to the empirical cumulative distribution function, and hence $F_{i,t}$ can be interpreted as a percentile of the distribution of demeaned utilization rates. The vector of controls $Z_{i,t}$ includes interactions of $\Delta g_{i,t-1}$, $\Delta\xi_{i,t}$, ,$\Delta\pi_{i,t}$, $\Delta\ln Q_{i,t}$, and $\Delta\ln\frac{w_{i,t}L_{i,t}}{X_{i,t}}$ with $1-F_{i,t-1}$ and $F_{i,t-1}$ as well as the main effect of $F_{i,t-1}$. Because $\Delta g_{i,t}=\frac{G_{i,t}-G_{i,t-1}}{X_{i,t-1}}$, the impulse response coefficients α_h^L for low initial utilization rates and α_h^H for high initial utilization rates are interpreted as dollar-for-dollar changes. We continue to include industry fixed effects, time fixed effects, and the interaction of time fixed effects with the foreign sales share. Adding the effective exchange rate to the specification makes little difference.

We construct Bartik-type instruments for defense spending at the industry level similar to Nakamura and Steinsson (2014) and Boehm (2016). Let G_t and X_t denote real defense spending and real gross output of all of U.S. manufacturing. The instrument is then the average pre-sample share of government purchases multiplied by change in defense spending on all of manufacturing. Formally, the instrument for industry i is

$$\frac{1}{6}\sum_{\tau=1966}^{1971}\frac{G_{i,\tau}}{X_{i,\tau}}\times\frac{G_t-G_{t-1}}{X_{t-1}}, \quad t=1972,...,2011.$$

Figure 3: Impulse response functions for a government spending shock



Notes: The impulse response coefficients are obtained via local projections using specification (25) with the controls $Z_{i,t}$ as described in the text. The shaded areas represent one standard error bands, based on standard errors that are clustered at the industry level. Impulse response functions for high utilization correspond to setting $F_{i,t-1} = 1$ and low utilization to setting $F_{i,t-1} = 0$.

As in Nakamura and Steinsson (2014) and Boehm (2016) all diagnostics suggest that the instruments are strong. We report them in Appendix C.1.

5.3 Results

Figure 3 shows the impulse response functions for defense spending, real gross output, and prices. A one dollar increase in defense spending is followed by additional spending in subsequent years. Over the course of the sample period, increases in spending that started at low initial levels of utilization were followed by somewhat higher spending one and two years after the shock. Cumulative spending over the first four years, including the impact year, is comparable: 3.83$ for high initial utilization rates versus 3.67$ for low initial utilization rates.

Industry gross output rises only when the initial capacity utilization rate is low. This is consistent with the earlier findings that were based on exchange rate variation and suggests that our finding of state-dependent responses to demand shocks is robust. Notice, however, that the standard errors are very wide, in particular for high initial utilization rates. (The shaded areas represent one standard deviation error bars.) The estimated multiplier for industry gross output when the initial utilization rate is low is 1.16 at a time horizon of 2 years and 0.9 at a time horizon of 3 years. The multipliers for high initial utilization rates are negative, but the standard errors are too large to reject the null hypothesis of equal multipliers at high and low initial levels of capacity utilization.

As the rightmost panel of figure 3 shows, prices rise when the spending shock occurs at high initial utilization rates and the response is significant at the 5 percent level one year after the shock. This impulse response is estimated using specification (25) after replacing the dependent variable with the percent change in prices. The response is insignificant if the spending shock occurs at low levels of capacity utilization. Note that these findings are again consistent with our earlier findings.

We discuss in the Appendix C several robustness checks, including a sample split depending on whether the initial utilization rate is above or below its median. The results are very similar and reported in figure C1.

6 Conclusion

This paper studies whether responses to demand shocks are state-dependent. To guide our empirical analysis we develop a putty-clay model in which short-run capacity constraints generate a convex supply curve at the industry level. Using a sufficient statistics approach, we estimate the model and find strong support for state-dependent responses to demand shocks. Industries with low initial capacity utilization rates expand production much more after dollar depreciations or defense spending shocks than industries that produce close to their capacity limit. Further, prices rise after such demand shocks only if the initial level of capacity utilization is high. Our evidence is consistent with convex supply curves at the industry level and suggests that capacity constraints are a likely candidate for generating state-dependent responses to shocks.

To be completed.

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A Appendix: Model Extensions

B Data Appendix

B.1 Sample and data sources

Our baseline sample is annual and includes all 21 3-digit NAICS manufacturing industries. It ranges from 1972 to 2011.

The sales shares $s_{i,n,t}$ are constructed based on sales to all countries that joined the OECD prior to year 2000. These are Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, the Republic of Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States. Sales to other countries, not included in the list, are counted as sales to the U.S.

C Appendix: Additional Results

Table C1: Summary Statistics of Utilization Rates by 3-digit NAICS Manufacturing Industries

Industry	NAICS	p10	Median	p90	Mean	S.D.	Skewness	Kurtosis	Durable
Food	311	79.6	82.3	85.2	82.4	2.4	0.3	2.5	no
Beverage and Tobacco Products	312	68.3	79.2	83.0	77.3	5.3	-0.5	2.1	no
Textile Mills	313	68.3	82.0	89.5	79.8	8.6	-0.8	3.2	no
Textile Product Mills	314	69.8	82.3	90.4	80.9	8.3	-0.8	3.2	no
Apparel	315	71.0	80.2	84.2	79.0	4.9	-0.9	3.4	no
Leather and Allied Products	316	59.3	74.9	82.1	72.8	8.8	-1.2	3.7	no
Wood Products	321	63.8	79.2	85.2	77.1	8.4	-1.2	4.6	yes
Paper	322	81.4	87.6	91.4	86.9	4.2	-0.2	2.4	no
Printing and Related Support Activities	323	72.2	82.7	89.3	81.3	7.6	-1.0	3.8	no
Petroleum and Coal Products	324	77.3	87.1	92.6	85.7	5.8	-0.7	2.8	no
Chemicals	325	72.1	77.8	83.1	77.7	4.3	-0.4	2.3	no
Plastics and Rubber Products	326	71.4	83.7	89.6	82.4	7.2	-0.9	3.3	no
Nonmetallic Mineral Products	327	62.3	77.2	84.0	75.3	9.2	-1.6	5.3	yes
Primary Metals	331	68.2	79.6	89.5	79.3	9.3	-0.7	3.4	yes
Fabricated Metal Products	332	71.7	77.7	84.4	77.4	5.7	-0.2	3.1	yes
Machinery	333	67.6	78.9	87.0	77.8	7.8	-0.2	2.5	yes
Computer and Electronic Product	334	70.1	79.0	84.2	78.2	5.7	-1.0	4.0	yes
Electrical Equipment, Appliances, and Components	335	73.2	82.8	90.6	82.6	6.7	-0.2	2.6	yes
Transportation Equipment	336	66.4	75.6	81.5	74.4	6.1	-1.0	4.1	yes
Furniture and Related Products	337	68.0	77.8	84.1	76.8	7.4	-0.2	3.9	yes
Miscellaneous	339	72.8	76.9	79.7	76.3	3.1	-0.5	3.1	yes
All		70.0	79.8	88.6	79.1	7.6	-0.8	4.4	

Source: Federal Reserve Board

C.1 First-Stage Regressions

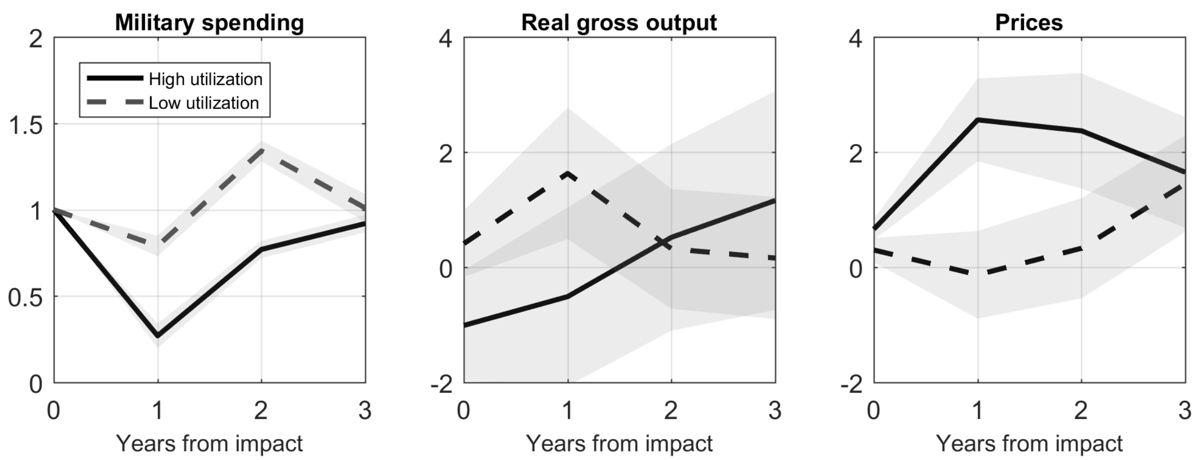
Table C2: First Stage Regressions for Government Spending

VARIABLES	$F_{i,t-1}\Delta g_{i,t}$	$(1-F_{i,t-1})\,\Delta g_{i,t}$	$F_{i,t-2}\Delta g_{i,t-1}$	$(1-F_{i,t-2})\,\Delta g_{i,t-1}$
$F_{i,t-1}\frac{1}{6}\sum_{\tau=1966}^{1971}\frac{G_{i,\tau}}{X_{i,\tau}}\times\frac{G_t-G_{t-1}}{X_{t-1}}$	7.30***	0.43	-2.33***	-0.75**
	(0.63)	(0.33)	(0.68)	(0.35)
$(1-F_{i,t-1})\,\frac{1}{6}\sum_{\tau=1966}^{1971}\frac{G_{i,\tau}}{X_{i,\tau}}\times\frac{G_t-G_{t-1}}{X_{t-1}}$	-0.04	6.15***	-0.02	-1.53***
	(0.32)	(0.38)	(0.22)	(0.35)
$F_{i,t-2}\frac{1}{6}\sum_{\tau=1966}^{1971}\frac{G_{i,\tau}}{X_{i,\tau}}\times\frac{G_{t-1}-G_{t-2}}{X_{t-2}}$	-1.36***	-0.18	7.16***	-1.70***
	(0.38)	(0.24)	(0.43)	(0.41)
$(1-F_{i,t-2})\,\frac{1}{6}\sum_{\tau=1966}^{1971}\frac{G_{i,\tau}}{X_{i,\tau}}\times\frac{G_{t-1}-G_{t-2}}{X_{t-2}}$	-0.52***	-2.95***	0.06	8.68***
	(0.16)	(0.42)	(0.15)	(0.30)
$F_{i,t-1}\Delta\ln\xi_{i,t}$	-0.14	0.38	0.05	0.35
	(0.09)	(0.23)	(0.14)	(0.26)
$(1-F_{i,t-1})\,\Delta\ln\xi_{i,t}$	-0.11	0.40	-0.01	0.33
	(0.09)	(0.24)	(0.13)	(0.26)
$F_{i,t-1}\Delta\ln\pi_{i,t}$	0.00	0.04	0.09	0.11
	(0.07)	(0.15)	(0.07)	(0.10)
$(1-F_{i,t-1})\,\Delta\ln\pi_{i,t}$	0.01	0.11	0.05	0.12
	(0.06)	(0.16)	(0.06)	(0.10)
$F_{i,t-1}\Delta\ln Q_{i,t}$	0.02**	-0.01***	0.01	-0.01*
	(0.01)	(0.00)	(0.01)	(0.01)
$(1-F_{i,t-1})\,\Delta\ln Q_{i,t}$	-0.00	0.00	-0.02**	-0.02
	(0.00)	(0.01)	(0.01)	(0.02)
$F_{i,t-1}\Delta\ln\frac{w_{i,t}Li,t}{X_{i,t}}$	-0.00	0.00**	-0.01***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
$(1-F_{i,t-1})\,\Delta\ln\frac{w_{i,t}Li,t}{X_{i,t}}$	0.00	-0.01***	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.01)
$F_{i,t-1}$	0.00	0.00*	-0.00**	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	819	819	819	819
R-squared	0.627	0.568	0.617	0.636
Industry FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Time FE * foreign sales share	yes	yes	yes	yes
Angrist-Pischke F-statistic	197.22	9.26	205.53	43.43

Notes: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The underlying sample corresponds to the first stage at horizon 0.

C.2 Additional results for government spending

Figure C1: Impulse response functions for a government spending shock



Notes: The impulse response coefficients are obtained via local projections. The shaded areas represent one standard error bands, based on standard errors that are clustered at the industry level.