Is Firm Pricing State or Time-Dependent?†

Evidence from US Manufacturing

Virgiliu Midrigan*

Department of Economics, Ohio State University

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Abstract

If firm pricing is state, rather than time-dependent, firms are more likely to change prices whenever aggregate and idiosyncratic shocks reinforce each other and trigger desired price changes in the same direction. The distribution of idiosyncratic shocks across adjusting firms therefore varies over time in response to economy-wide disturbances: in times of, say, monetary expansions, the fraction of adjusting firms that have negative idiosyncratic technology shocks should increase. Using measures of technology shocks derived from production function estimates for four-digit US manufacturing industries, we find that sectoral inflation rates are more responsive to negative, as opposed to positive technology disturbances in periods of higher economy-wide inflation, commodity price increases and expansionary monetary policy shocks. We argue, using a quantitative state-dependent sticky price model calibrated to match key features of the US micro-price data, that these results suggest that pricing is state-dependent in US manufacturing.

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*Correspondence: Arps 410, 1945 N. High St., Columbus, OH, 43210, midrigan.1@osu.edu

1. Introduction

Money and real activity are strongly correlated at business cycle frequencies. The strength of this correlation has led the profession to a widespread use of models employing nominal rigidities in an attempt to explain salient macroeconomic phenomena. Two distinct approaches to modeling nominal rigidities have been used in earlier work. The first approach, exemplified by the work of Fisher (1977) and Taylor (1980), assumes that the timing of price changes is independent of shocks affecting the firm in each period. Institutional restrictions or information-gathering costs prevent firms from meeting too often and instead, firms have predetermined schedules of price adjustment. These are the so-called time-dependent models, which, because of their computational tractability, have received most of the profession's attention in the last two decades. The second tradition, dating back to Sheshinski and Weiss (1977), assumes that observing the state of the world is inexpensive, but that firms incur fixed physical costs of price adjustment every time they undergo a new price change. This second generation of models, the so-called state-dependent models, are grounded in solid micro-foundations as they explicitly model the source of nominal rigidities, but have been, with a few notable exceptions, neglected by the profession because of their computational complexity.

Despite the fact that most policy-oriented macroeconomic models use the time-dependent assumption of an exogenous timing of price changes, the distinction between state and time-dependent sticky price models is not innocuous. Caplin and Spulber (1987) show that under special assumptions about the distribution of firm prices and the stochastic process of the money supply, a monetary expansion has no effect on output: although few firms adjust in response to the shock, the firms that do adjust are those that need the largest changes in their nominal prices and the aggregate price level in their economy grows at the same rate as the money supply. Recent research, grounded in explicit household and firm maximization, and using more realistic stochastic forcing processes calibrated from the US data, has overturned this neutrality result, but nevertheless reaches the conclusion that state-dependent pricing models generate smaller real effects from monetary shocks. In Dotsey, King and Wolman (1999), firms synchronize prices in response to aggregate disturbances, and increase price in tandem in response to large aggregate disturbances. Golosov and Lucas (2004) solve a state-dependent pricing model in which firms are subject to marginal cost shocks and find that the model, calibrated to match microeconomic data on the size and frequency of price changes, generates very little output volatility.

Given that time and state-dependent sticky price models produce different implications regarding the ability of nominal disturbances to explain business cycle fluctuations, an important question that, with a few exceptions, has received little attention is: is firm pricing state or time-dependent? Time-dependent rules are optimal if firms incur information-gathering costs that prevent them from observing the state of the world each period[1]. On the other hand, firms follow state-dependent rules if fixed physical costs of price changes are mainly responsible for nominal rigidities. Recent evidence suggests that time-dependent rules are the rule, rather than exception. Zbaracki et. al. (2004) study the price adjustment practices of a large US manufacturing firm. The firm under consideration revises prices infrequently, once every year, during a "pricing season", which generally occurs at the same time during the year, from August to November. Blinder et. al. (1998) use survey evidence collected from a national, multi-industry sample of 200 CEOs and find that time-dependent rules of price adjustment are twice as common as state-dependent rules. Klenow and Kryvtsov (2004) draw a similar conclusion by calibrating a state-dependent model to match the fact that firms do not synchronize their price changes in response to aggregate shocks in the US economy. They find that a state-dependent model can be made consistent with this finding if the distribution of menu costs a firm faces each period is (close to) degenerate at two mass points and firms face either zero or very large menu costs, which leads them to behave similarly to firms in a Calvo-type environment in which the timing of price adjustment is exogenous[2]. A final piece of evidence is the work of Cecchetti (1986) and Kashyap (1995) who study newspaper and catalogue prices, respectively, and find that the frequency of price changes increases during periods of higher overall inflation. This evidence alone cannot however distinguish between time and state-dependent pricing models. Although simple time-dependent models indeed postulate an exogenous frequency of price changes, firms that face information-gathering costs and behave in a time-dependent fashion would choose to increase the frequency of price changes in environments of higher inflation if the source of nominal rigidities were explicitly modeled.

In this paper we use indirect evidence based on sectoral inflation rates in 450 SIC four-digit manufac-

[1] See for example Bonomo and Cavalho (2004).

[2] Although, as Golosov and Lucas (2004) show, a state-dependent model in which firms face volatile marginal cost shocks can also generate little synchronization of firms in response to economy-wide disturbances even if menu costs are time-invariant.

turing sectors in order to test whether firm pricing is time or state-dependent. Unlike earlier, survey-based studies, we rely on a larger sample of firms, spanning 40 years of data and a large subset of the US economy in order to conduct inference. Our tests are based on the following premise. If firm pricing is state-dependent, the firm's decision to adjust is based on not only their idiosyncratic but also the aggregate shock in the economy. The firms for which the two types of disturbances reinforce each other and trigger desired price changes in the same direction are more likely to adjust and pay the menu costs. Consider for example an environment in which firms face idiosyncratic technological disturbances as well as aggregate, monetary shocks. In periods of monetary expansions, firms are more likely to adjust if idiosyncratic shocks reinforce the incentive to increase prices arising from the monetary disturbance. Most of adjusting firms in such periods should then be firms with negative technological shocks. In contrast, if pricing is time-dependent, the distribution of technology shocks among adjusting firms should be irresponsive to economy-wide disturbances.

A direct test of this implication of state-dependent models requires firm-level data on actual prices and technology (or other marginal cost) disturbances, data generally unavailable for a large segment of the economy. We rely instead on sectoral price, input and output data available from the NBER Manufacturing Productivity Database. We use this data to calculate a measure of technological disturbances based on sectoral production function estimates that explicitly allow for increasing returns, imperfect competition and variable capacity and labor utilization, using the approach of Basu and Kimball (1997). We use these measures of technology shocks to ask whether economy-wide disturbances alter the responsiveness of sectoral inflation rates to negative, relative to positive technology disturbances. We find that they do: sectoral inflation rates are much more responsive to negative, as opposed to positive technology shocks in periods with greater than average aggregate inflation, larger changes in commodity prices and monetary policy shocks. This evidence strongly supports the state-dependent hypothesis, as it implies that the timing of price changes is endogenous, and responds to both aggregate and idiosyncratic (sectoral) shocks.

This paper is related to the work of Ball and Mankiw (1994,1995), Danziger (1999), as well as Golosov and Lucas (2004). Ball and Mankiw (1994) show that in the presence of non-stochastic trend inflation, an increase in the volatility of idiosyncratic shocks is inflationary, as most of the firms that adjust in an environment with positive trend inflation and menu costs of price changes are firms that desire price increases.

Similarly, changes in the skewness of the distribution of idiosyncratic shocks can also cause movements in the aggregate price level if pricing is state-dependent, as in Ball and Mankiw (1995). In contrast, this paper studies a different implication of state-dependent models, generated again by the endogenous timing of price changes: we ask whether the distribution of idiosyncratic shocks, conditional on adjustment, varies over time in response to monetary and other types of aggregate disturbances. Danziger (1999) and Golosov and Lucas (2004) study the general equilibrium implications of models with state-dependent pricing, idiosyncratic technology shocks and aggregate monetary disturbances. An implication of these models is that money is close to neutral, despite nominal rigidities at the firm level, a result arising from the asymmetric response of firms hit by negative versus positive technology shocks to a monetary expansion[3]. An increase in the money supply forces adjustment by mostly negative-shock firms and acts as an adverse "supply" shock that offsets the expansionary effect of the increase in real balances.

The rest of this paper is organized as follows. Section 2 presents a partial equilibrium model in which menu costs of price changes lead firms to follow state-dependent rules of price adjustment. We use the model in order to validate our empirical approach: we use it to derive a proxy for the distribution of idiosyncratic shocks conditional on adjustment. In Section 3 we discuss the data we use in this paper and the methodology used to calculate measures of technology shocks. Section 4 tests the state-dependent pricing model. The final section concludes.

2. A test of State-Dependent Pricing Models

In this section we discuss one source of asymmetry implied by the endogenous timing of firm price adjustments in menu-cost models, an asymmetry that we explore in our empirical work in the next section. To fix ideas, we first discuss the source of asymmetry heuristically, and illustrate how the distribution of idiosyncratic shocks among adjusting firms fluctuates in response to economy-wide shocks. We then formally solve a partial equilibrium problem in which a continuum of firms face idiosyncratic and sectoral technology shocks, as well as monetary policy shocks and illustrate the role of the asymmetries quantitatively.

[3]Midrigan (2005) shows that 80% of the variability of inflation in a general equilibrium model with idiosyncratic and aggregate shocks, calibrated to match key features of the US micro-price data, is due to the endogenous variation of the identity of adjusting firms in response to aggregate shocks.

A. Heuristic Example

The logic behind out test of whether pricing is state or time-dependent is simple. Consider an industry j, in which a continuum of firms, indexed by i, faces menu costs of changing their prices. We assume, to build intuition, that firms follow simple, symmetric S-s pricing rules of price adjustment:

$$\begin{aligned} \pi_{ijt} &= \pi^*_{ijt} \text{ if } \pi^*_{ijt} \notin [-s, s] \\ \pi_{ijt} &= 0, \text{ otherwise,} \\ \pi^*_{ijt} &= u_{ijt} + \varepsilon_{jt} + g_t, \end{aligned} \tag{1}$$

where π^*_{ijt} is the firm's desired price change in a frictionless world, π_{ijt} is the actual price change, s is the maximum deviation of its price from the optimum that the firm tolerates, g_t is an aggregate disturbance, ε_{jt} an industry-wide shock, and u_{ijt} a firm-specific disturbance that captures both contemporaneous shocks to the firm's desired price, but also the history of all shocks since the previous price adjustment. As long as u_{ijt} are centered around 0, and not too dispersed to drive most of the adjustment, firms in sectors in which the sectoral ε_{jt} and aggregate shocks g_t are of the same sign are more willing to change prices than sectors in which the two shocks cancel each other out.

Letting $\Theta(\varepsilon_{jt}, g_t) = \{u_{ijt} | u_{ijt} \leq -s - (g_t + \varepsilon_{jt}) \text{ or } u_{ijt} > s - (g_t + \varepsilon_{jt})\}$ denote the firm's adjustment region, the probability that a firm adjusts (which, invoking a law of large numbers, is also the fraction of firms that adjust in a given sector) $\mathcal{F}r(\varepsilon_{jt}, g_t) = \text{Prob}[u_{ijt} \in \Theta(\varepsilon_{jt}, g_t)]$, increases if $g_t + \varepsilon_{jt}$ is large in absolute value.

This observation suggests a way of testing whether firm pricing is state or time-dependent. What differentiates the two approaches to modelling nominal rigidities is the fact that the timing of price changes is exogenous in time-dependent models and thus unresponsive to idiosyncratic or aggregate disturbances. In the language of the example above, the probability that a firm adjusts is independent of g_t and ε_{jt}. In contrast, state-dependent firms are more likely to adjust in a given period if $g_t + \varepsilon_{jt}$ has a large absolute value, i.e., the aggregate and sectoral shock trigger desired price changes in the same direction.

To test the prediction above using data available for the US economy, we need a proxy for the fraction of adjusting firms in a given sector. We use the fact that, in a sticky price model, sectoral inflation rates are more responsive to sectoral and aggregate shocks the larger the fraction of firms adjusting in this sector. To see this, let $\pi_{jt} = \frac{1}{N}\sum_{i=1}^{N} \pi_{ijt}$ be the inflation rate of sector j. Substituting the policy rule assumed above into this expression yields

$$\pi_{jt} = \mathcal{F}r(\varepsilon_{jt}, g_t)\,(\varepsilon_{jt} + g_t) + \frac{1}{N}\sum_{i=1}^{N} u_{ijt}\mathcal{I}(u_{ijt} \in \Theta(\varepsilon_{jt}, g_t)), \tag{2}$$

where $\mathcal{I}$ is an indicator function. The first term in this expression is the fraction of adjusters times the desired price change arising from aggregate or sectoral disturbances. The second term is a "selection bias" term: firms are more likely to adjust if their idiosyncratic shocks are aligned with ε_{jt} and g_t. We will employ a regression of sectoral inflation rates on aggregate and sectoral disturbances:

$$\pi_{jt} = \Gamma\left(\varepsilon_{jt}, g_t\right)(\varepsilon_{jt} + g_t) + \text{error}_{jt}, \tag{3}$$

where $\Gamma\left(\varepsilon_{jt}, g_t\right)$ is a non-linear function of the two disturbances, in order to test the state-dependent model. Although $\Gamma\left(\varepsilon_{jt}, g_t\right)$ in such a regression provides an estimate of $\mathcal{F}r(\varepsilon_{jt}, g_t)$ that is upward biased, because of the selection term in (2) above, note that we are not interested in the fraction of adjusters itself, but rather in the properties of the set $\Theta(\varepsilon_{jt}, g_t)$. If pricing is indeed state-dependent, and aggregate and sectoral shocks reinforce each other, a sector's responsiveness to observable disturbances, $\Gamma\left(\varepsilon_{jt}, g_t\right)$, increases both because the fraction of adjusters in the industry increases, but also because the firms that do adjust are those whose idiosyncratic shocks, u_{ijt}, trigger desired price changes in the same direction as sectoral and aggregate shocks. In contrast, if the timing of price changes is exogenous, $\Gamma\left(\varepsilon_{jt}, g_t\right)$ is constant in its two arguments.

Our empirical approach is therefore based on estimating elasticities that capture the responsiveness of sectoral inflation rates to sectoral technology shocks and aggregate monetary disturbances, and testing whether these elasticities are a non-linear function of the two types of shocks. Our null hypothesis is that the inflation rates in equation (3) are a linear function of disturbances, i.e., that firms change prices in a time-dependent fashion. Non-linearities in the responsiveness of firms to shocks can arise however even if the timing of price changes is exogenous, but price functions, conditional on adjustment, are non-linear, contrary to what we have assumed in (1) above. The model of the next subsection provides a formal justification for the empirical approach in this paper. In particular, we solve two sticky price models, one in which firms set prices in a Calvo (1983) fashion, and another one, in which menu costs of price changes are responsible for nominal rigidities. We solve the two models using projection-based functional approximation techniques that explicitly allow for non-linearities and calibrate the models in order to allow them to match important features of the micro-price data, stressed by Klenow and Kryvtsov (2004) and Golosov and Lucas (2004). We find that non-linearities in the pricing function of a Calvo-type firm are absent, which implies that an estimate of equation (3) using data generated by a simulation of a time-dependent model contains no non-linear terms. In contrast, non-linearities are evident in a state-dependent setup, suggesting that the intuition developed above holds in a more realistic class of models than the simple illustrative example considered above.

B. A Partial Equilibrium Model

Our model is similar to the partial equilibrium problem studied by Sheshinski and Weiss (1977). We allow however the general price level to grow at a stochastic, possibly negative, rate and assume that in addition to aggregate shocks, firms face idiosyncratic and aggregate disturbances to their marginal costs. Let $\bar{p}_t$ be the general price level in the economy, assumed to evolve exogenously, according to $\bar{p}_t = \bar{p}_{t-1}e^{g_t}$, where the growth rate of the price level is driven by $g_t = \alpha + \delta g_{t-1} + \eta_t$, with $\eta_t \sim N(0, \sigma_\eta^2)$. We interpret η_t as monetary policy shocks. Letting $z_t = \frac{p_t}{\bar{p}_t}$, where p_t is the firm's nominal price and z_t its real price, we assume constant elasticity demand functions: $q_t = z_t^{-\theta}$.

The firm's real profits in period t are: $\Pi(z_t) = z_t^{-\theta}\left(z_t - \frac{c}{a_t}\right)$, where $\frac{c}{a_t}$ is the (real) marginal cost of production, and a_t is the firm's technology[4]. The firm's technology is the product of an idiosyncratic and sectoral component: $a_t = \psi_t \phi_t$, which evolve according to $\log(\psi_t) = \rho \log(\psi_{t-1}) + \varepsilon_t$ and $\log(\phi_t) = \rho \log(\phi_{t-1}) + u_t$, where ε_t is a sectoral and u_t a firm-specific technology shock. We assume for simplicity that the two components of a firm's technology have the same degree of serial correlation, and the shocks are drawn from a Gaussian distribution with mean 0 and variance σ_ε^2 and σ_u^2 , respectively.

[4] We supress the sector and firm subscripts to conserve notation and revert to them below when needed.

State-Dependent Pricing

In this setup firms face costs of adjusting nominal prices. Specifically, a firm incurs cost ξ[5] every period in which $p_t \neq p_{t-1}$. The firm's problem is to

$$\max_{z_t} E_0 \sum_{t=0}^{\infty} \beta^t \left[\Pi(z_t) - \xi \mathcal{I}\left(z_t \neq \frac{z_{t-1}}{e^{g_t}} \right) \right], \tag{4}$$

where $\mathcal{I}()$ is an indicator function.

Let $V^a(z_{-1}, \psi, \phi, g), V^n(z_{-1}, \psi, \phi, g)$ denote the firm's value of adjusting and not adjusting its nominal price, respectively, where z_{-1} is the firm's last period's relative price: $p_{t-1}/\bar{p}_{t-1}$. Let $V = \max(V^a, V^n)$ denote the firm's value function and $s_t = (z_{t-1}, \psi_t, \phi_t, g_t)$ collect the state variables. The solution to the firm's problem satisfies the following system of functional equations:

$$V^a(s) = \max_z \left[z^{-\theta} \left(z - \frac{c}{\psi\phi} \right) - \xi + \beta \int_{\varepsilon \times u \times \eta} V\left(s'\left(z, s, \varepsilon, u, \eta \right) \right) dF(\varepsilon, u, \eta) \right], \tag{5}$$

$$V^n(s) = \left[\left(\frac{z_{-1}}{e^g} \right)^{-\theta} \left(\frac{z_{-1}}{e^g} - \frac{c}{\psi\phi} \right) + \beta \int_{\varepsilon \times u \times \eta} V\left(s'\left(\frac{z_{-1}}{e^g}, s, \varepsilon, u, \eta \right) \right) dF(\varepsilon, u, \eta) \right],$$

where $F()$ is the joint cdf of the three shocks, and $s'()$ is the law of motion for the state variables. The real price the firm faces at the start of the next period is equal to either $z'_{-1} = z$ if the firm adjusts the nominal price and pays the menu cost, or eroded by the growth rate of the general price level and equal to $z'_{-1} = \frac{z_{-1}}{e^g}$.

Calvo Time-Dependent Pricing

In this exercise we assume that firms have no control over the timing of their price changes. Rather, the probability that a firm adjusts in a given period is constant, and equal to λ. The two functional equations

[5] We interpret menu costs as costs of physically changing the price and transmitting the information about the price change to the consumer. Zbaracki et. al (2004) find that these costs are non-trivial. For example, costs of transmitting the information regarding price changes to consumers constitute 0.4% and 1.8% of total revenues and operating expenses, respectively, for the firm in their study.

characterizing the firm's problem in this setup are:

$$V^a(s) = \max_z \left[z^{-\theta}\left(z - \frac{c}{\psi\phi}\right) + \beta \int\limits_{\varepsilon\times u\times\eta} V\left(s'\left(z, s, \varepsilon, u, \eta\right)\right) dF(\varepsilon, u, \eta) \right],$$

$$V^n(s) = \left[\left(\frac{z_{-1}}{e^g}\right)^{-\theta}\left(\frac{z_{-1}}{e^g} - \frac{c}{\psi\phi}\right) + \beta \int\limits_{\varepsilon\times u\times\eta} V\left(s'\left(\frac{z_{-1}}{e^g}, s, \varepsilon, u, \eta\right)\right) dF(\varepsilon, u, \eta) \right],$$

where $V(s) = \lambda V^a(s) + (1-\lambda)V^n(s)$.

To solve these problems, we employ collocation, a functional approximation technique. The idea behind this method is to approximate the two value functions with a linear combination of orthogonal (we employ Chebyshev) polynomials and solve for the unknown coefficients by requiring that the two equations are satisfied exactly at a number of nodes along the state-space. A technical appendix discusses the solution method and its accuracy in more detail.

We assign the model parameter values to ensure that the predictions of the state-dependent model match certain features of the US economy. The length of the period is a month. We interpret shocks to the growth rate of the price level as monetary shocks and calibrate this process by estimating an AR(1) process for the monthly growth rate of the US money supply[6]. The elasticity of demand, θ, is chosen so that the steady-state markup is equal to 25%[7]. We assume that idiosyncratic and sectoral technology shocks are equally volatile[8], and calibrate the size of the menu costs ξ and the volatility of technology shocks to ensure that firms adjust on average every five months and, when they do so, change prices by $\pm 10.5\%$ on average[9]. We set $\rho = 0.8$ for the experiments reported in this paper, but our results are robust to alternative choices of the degree of serial correlation in technology. In particular, we have also experimented with iid and unit-root

[6]M1data, 1959 to 2004. There is substantial noise in the growth rate of the money supply at the monthly frequency, which biases downward the AR(1) coefficient of the growth rate of the money supply. Results are robust however in simulations of the model using different degrees of serial correlation in g_t, or a more appropriate ARMA(1,1) process for g_t. We have also experimented with an AR(1) process for the growth rate of the US CPI and obtained similar results to those reported below.

[7]This number is in line with elasticity of substitution estimates in earlier work, which range from $\theta = 3$ to $\theta = 6$. See Obstfeld and Rogoff (2000) for a brief survey.

[8]We have redone our work by assuming that idiosyncratic shocks are five times more volatile than sectoral shocks. In this case the results discussed below are weaker (because the importance of the "selection bias" term associated with firm-specific (as opposed to aggregate or sectoral) shocks increases), but still statistically significant. In a sense, the empirical approach of this paper tests the joint hypothesis that pricing is state-dependent and that sectoral shocks sufficiently large relative to idiosyncratic shocks for us to be able to discern the non-linearities implied by state-dependent pricing rules.

[9]These numbers are similar to those reported by Bils and Klenow (2002) and Klenow and Kryvtsov (2004), based on two large datasets of consumer prices made available by BLS.

technology processes and found similar results. The probability that a Calvo firm adjusts in a given period is chosen so that the state and time-dependent models predict the same frequency of price changes: $\lambda = .2$.

The table below summarizes the parameter values we use. The menu cost, ξ, is equal to $0.0132c$, that is, 1.32% of the firm's steady-state total cost of production.

β	α	δ	σ_η^2	ρ	$\sigma_\varepsilon^2, \sigma_\eta^2$	ξ	θ
.997	$1.9{\times}10^{-3}$	0.55	$2.75{\times}10^{-5}$	0.8	$1.1{\times}10^{-3}$	$0.0132c$	5

We start by discussing the price functions that solve the firm's problem. Figure 1 plots the optimal price (conditional on adjustment) of a firm, expressed as the log-deviation of the firm's real price from its steady-state optimum: $\log(z_t/(\frac{\theta}{\theta-1}c))$, as a function of the firm's technology, for two values of the growth rate of the price level. Note two differences in the pricing functions of a Calvo and state-dependent firm. First, a state-dependent firm responds more strongly to a technology shock (the elasticity is close to -1, similar to what it would be in a flexible price model in which prices are a constant markup over marginal cost) than Calvo firms do (the elasticity is close to -.5). Second, Calvo firms respond more aggressively to an increase in the growth rate of the price level than state-dependent firms do. These differences in price functions arise because of the type of nominal frictions Calvo and menu cost firms are subject to. If a Calvo firm finds itself with a suboptimal price in a given period in the future, it pays dearly: given that it will not re-adjust its price for an average of 5 months, it will incur losses from the suboptimal price for a number of periods to come. In contrast, a state-dependent firm can always choose to pay the menu cost and reprice: its losses from having a suboptimal price in future periods are smaller than those of a time-dependent firm. This in turn implies that a Calvo firm has a stronger incentive to offset future expected changes in its marginal cost every time it adjusts than a state-dependent firm does. Calvo firms therefore respond less aggressively to a technology shock (as the level of technology, by assumption, reverts to its mean), and more aggressively to a shock to the growth rate of the price level (because the price level growth rate is serially correlated and a high inflation rate today predicts higher than average inflation in future periods). We illustrate this idea graphically in Figure 2: a firm's value of inaction is much more responsive to deviation of its past price from the optimum if a firm is subject to Calvo-type frictions than menu costs of adjusting prices. For this reason, state-dependent firms behave as if they discount the future less than Calvo firms do and set a price that resembles the price they would charge in a flexible price world.

The most important lesson to be learned from the discussion above is that in both Calvo and state-dependent pricing models, a firm that decides to adjust its price responds in a linear fashion to aggregate and sectoral disturbances. As Figure 1 indicates, the slope of the firm's optimal price in its technology level is constant, and moreover, unaffected by the size of the aggregate disturbance. Non-linearities in the sector's responsiveness to sectoral and aggregate shocks may only arise, then, if the fraction of adjusting firms and their identity varies endogenously, as in a state-dependent model[10].

Figure 3 plots the fraction of adjusters $\mathcal{F}r(\varepsilon_{jt}, g_t)$ in a sector hit by a technology shock ε_{jt}[11], as a function of the growth rate of the general price level, for the state-dependent pricing model. Consider first sectors subject to negative technology disturbances ($\varepsilon = -.07$ and $\varepsilon = -.04$). Firms in these sectors desire, on average, to increase their prices in order to respond to the higher marginal costs of production. This incentive to change prices is reinforced if the economy-wide nominal shock is also positive. For this reason, the fraction of firms that adjusts in sectors with negative technology shocks increases in g, the growth rate of the general price level. Note also the difference in the slope of $\mathcal{F}r()$: an increase in g has a stronger effect on the fraction of adjusters in sectors subject to more negative technology disturbances.

In contrast, firms in sectors with positive technology shocks see their marginal cost falling and desire price decreases. Their desire to decrease real prices is automatically satisfied if the aggregate price level increases, thereby eroding the firm's real price. The fraction of firms that adjusts in sectors with positive technology disturbances therefore decreases as the growth rate of the economy-wide price level rises. Note again the difference in slopes: the larger the sector's technology shock is, the larger the effect aggregate disturbances will have on the fraction of adjusters in this particular industry.

The results presented in Figure 3 are not useful for empirical purposes, as we do not directly observe the fraction of firms that adjust in a given sector. We therefore estimate elasticities that capture the responsiveness of sectoral inflation rates to shocks and ask whether these elasticities vary in the data in a non-linear fashion.

[10] Asymmetries in a state-dependent model can arise for reasons other than fluctuations in the fraction and identity of adjusters in response to aggregate disturbances. For example, more productive firms are more willing to adjust prices as they prefer to "make hay while the sun is shining" – see the discussion in Golosov and Lucas (2004). These asymmetries are however absent in time-dependent models, which is the null hypothesis maintained in this paper.

[11] To calculate this statistic, we initialize the economy at its non-stochastic steady-state and integrate the decision rules of the firms in the industry by employing a Monte-Carlo simulation in which firm-specific shocks are drawn from $N(0, \sigma_u^2)$.

We use model-simulated data and estimate a panel regression of sectoral inflation rates against technology shocks and aggregate disturbances, a regression in which we allow elasticities to differ across observations with negative and positive sectoral technology shocks, and also according to whether the growth rate of the price level belongs to one of the 6 quantiles of its distribution.

$$\pi_{it} = \gamma(\varepsilon, g)\varepsilon_{it} + \beta g_t + u_{it} \tag{6}$$

where $\gamma(\varepsilon, g)$ takes on 12 different values depending on the whether ε is positive or negative, and the quantile of the distribution g belongs to[12]. Figure 4 plots the absolute values of the estimated elasticities on technology shocks, $\gamma(\varepsilon, g)$, in the g space, for both the state and time-dependent models. Note in the left panel of the figure that, when the growth rate of the price level is low, the estimated elasticity is 0.64 in absolute value for sectors subject to negative technology disturbances, and 0.78 for sectors with positive technology shocks. As the growth rate of the price level increases, firms in sectors with $\varepsilon < 0$ are more willing to adjust prices and the elasticity increases to 0.82. In contrast, the fraction of firms that adjust in positive shock sectors falls with the growth rate of prices, and their elasticity drops to 0.60 when aggregate shocks are in the upper quantile of their distribution. Note in the right panel of the figure that these elasticities are, given the exogenous timing of price changes and lack of non-linearities in the price function, constant in the time-dependent model. They are also much smaller, both because of the disincentive of Calvo firms to respond to shocks that are expected to mean-revert, but also because of the lack of a selection bias in a time-dependent model.

A more compact way to summarize the effect of aggregate and sectoral shocks on the responsiveness of sectoral inflation to disturbances is to simply look at the difference between the elasticities of sectoral inflation with respect to technology shocks in sectors with negative and positive technology shocks, as a function of the aggregate disturbance. To this end, we estimate the following period-by-period regressions:

$$\pi_{it} = c + \gamma_t^N \varepsilon_{it} \mathcal{I}(\varepsilon_{it<0}) + \gamma_t^P \varepsilon_{it} \mathcal{I}(\varepsilon_{it>0}) + u_{it} \tag{7}$$

[12] One can also allow the responsiveness to aggregate shocks, g_t, to vary non-linearly as well, but the fact that technology shocks, in both the model and the data, are much more volatile than nominal disturbances makes them a more suitable candidate for identifying the fraction and identity of firms that adjust in a given sector.

where γ_t^N and γ_t^P are the elasticities of sectoral inflation rates to positive and negative technology shocks in each period and $\mathcal{I}$ an indicator function. Figure 5 presents a scatter plot of $\gamma_t^P - \gamma_t^N$ as a function of the growth rate of the general price level in each period. Note that the difference in elasticities increases in the price level growth rate in the state-dependent model (the difference in the absolute value of elasticities falls as firms in sectors with positive technology disturbances adjust less willingly), while it is flat in the Calvo model.

Finally, we can allow the responsiveness of sectoral inflation rates to technology shocks to vary more continuously with the size of the sectoral technology shock and aggregate disturbances. Let

$$\pi_{it} = \gamma_0 + \Gamma\left(\varepsilon_{it}, g_t\right)\left(-\varepsilon_{it}\right) + \gamma_3 g_t + u_{it}, \tag{8}$$

where $\Gamma(\varepsilon, g)$ is a function that captures the responsiveness of a sector's inflation rate to aggregate and sectoral shocks due to changes in the fraction of adjusters, but also their identity, in response to disturbances. As shown above, the state-dependent model predicts that

$$\frac{\partial^2 \Gamma(\varepsilon, g)}{\partial\varepsilon\partial g} < 0,$$

as firms are more willing to change prices if sectoral technology shocks and aggregate disturbances reinforce each other and trigger desired price changes in the same direction. To capture this cross-partial derivative, we parameterize $\Gamma(\varepsilon, g) = \gamma_1 - \gamma_2\left(\varepsilon \times g\right)$, where γ_2 is expected to have a positive sign if pricing is state-dependent. Our test of state-dependent pricing can be based on the following regression:

$$\pi_{it} = \gamma_0 + \gamma_1(-\varepsilon_{it}) + \gamma_2\left(\varepsilon_{it}^2 \times g_t\right) + \gamma_3 g_t + u_{it} \tag{9}$$

3. Measures of technology shocks

A. Data

We test the predictions of the state-dependent pricing model using annual data from 1958 to 1996 for 446 4-digit SIC industries from the NBER Manufacturing Productivity Database[13]. The data is derived from various government sources, notably the Census Bureau's Annual Survey of Manufacturing, and contains information on total shipments, materials expenditure, investment, capital stock, number of production and non-production workers, payroll, production worker hours and wages, as well as price deflators for shipments, materials etc. for each industry. Material expenditures include expenditure on energy, and the deflator for materials accounts for movements in the price of energy. Bils and Chang (1999) is a recent example that uses this dataset in order to ask how industry prices respond to variations in costs and production, although, given our focus on asymmetries in response to purely technological shocks, our approach differs from theirs along several dimensions. We use this data in order to conduct our empirical exercises as discussed below.

B. Measuring technology shocks

Our measures of technology shocks are Solow (1957) residuals estimated using the methodology developed by Hall (1990) and Basu and Kimball (1997) in order to account for the possibility of increasing returns, imperfect competition and variable input utilization, respectively.

We assume a differentiable production function in which firms produce output Y, using capital services $\tilde{K}$, labor services $\tilde{L}$, intermediate inputs of materials and energy M according to:

$$Y = F(\tilde{K}, \tilde{L}, M, A)$$

Capital services depend on the stock of capital K, but also capital utilization $Z : \tilde{K} = ZK$, while labor services depend on the number of workers N, hours worked per employee H and each worker's effort level $E : \tilde{L} = ENH$. Taking logarithms of this production function, totally differentiating, and invoking cost

[13] The data is available at http://www.nber.org/nberces/nbprod96.htm and is discussed extensively in Bartelsman and Gray (1996). The industries are those defined in the 1972 Standard Industrial Classification. We drop two industries that have missing observations for several years.

minimization, one obtains:

$$dy = \mu \left[s_k dk + s_L(dn + dh) + s_m dm \right] + \mu \left[s_k dz + s_L de \right] + da$$

where lower case letters denote logs, s_j is the share of factor j in total revenue and μ is the markup . The difficulty in estimating this equation directly is that effort and capital utilization are not observed. We follow Basu and Kimball (1997) and proxy the unobserved input utilization with hours per worker dh[14]. The justification for this approach is that firms operate along all margins simultaneously, and given convex costs of changing hours worked, effort and capital utilization, will choose to change them simultaneously in response to a shock. Changes in hours worked are therefore correlated with unobserved capital utilization and effort. More formally, Basu and Fernald (2000) solve a dynamic cost minimization problem of a firm subject to costs of changing employment levels, hours worked and capital utilization, and show that as long as capital's depreciation rate does not depend on its utilization level and the production function is Cobb-Douglas, a log-linear approximation to the firm's optimality conditions implies that dz and de depend on dh only[15]. We therefore estimate

$$\Delta y_{it} = c_i + \mu \Delta x_{it} + \gamma \Delta h_{it} + \tilde{\varepsilon}_{it} \tag{10}$$

where Δy_{it} is the change in the log output of industry i, Δx_{it} is the share-weighted sum of the growth rate of real inputs (labor, capital, materials and energy). We calculate total output as shipments plus change in end-of-period inventories and deflate it using the price deflator for shipments. The Productivity Database distinguishes between production and non-production workers in reporting industry employment, and only reports hours data for production workers. We use the two as separate inputs in the production function and assume that hours per worker are time-invariant for non-production workers. Our results are robust to an

[14]Conley and Dupor (1999) use an alternative proxy for capital utilization, one based on electricity consumption. Electricity data is not available however at the 4-digit level of disaggregation.

[15]Allowing for depreciation rates to increase with capital utilization, as in Basu and Kimball (1997) complicates the problem as utilization will depend on material inputs, capital stock, investment and the relative price of materials and investment: $dz = A(d(p_m - p_I) + dm - dk) + B(di - dk)$. where $p_m - p_I$ is the relative price of materials and investment, i and k are investment and the stock of capital, respectively, A and B are constants. We have used this alternative proxy for capital utilization and found results to be very similar to those reported in text.

alternative measure of inputs that includes only production workers. Our proxy for variable input utilization, Δh_i, is the log-difference in hours per worker reported for production workers.

We calculate the share of each factor of production as the time-series average of total payments to each factor divided by total revenues in each industry. One could in principle depart from this Cobb-Douglas assumption of constant shares and allow shares to vary over time, but, as Basu and Fernald (2000) argue, this approach increases the likelihood of misspecification because observed factor prices are not allocative period-by-period in a world with implicit contracts or quasi-fixity[16]. To calculate payments to capital, we first calculate the user cost of capital, R, according to[17]:

$$R = (r + \delta)\frac{1 - ITC - \tau d}{1 - \tau}$$

where r is the required rate of return on capital (we follow Hall (1990) and assume it equal to the S&P 500 dividend yield), δ is the depreciation rate, ITC is the investment tax credit, d is the present-value of depreciation allowances and τ is the corporate income tax rate. Jorgenson and Yun (1991) provide data on ITC, d and δ for 53 types of capital goods, while the tax data is provided by the Bureau of Economic Analysis at the 2-digit level of disaggregation. We calculate the user cost of capital for each asset and a weighted average over the different types of assets for each SIC 2 industry in the dataset, with the weights reflecting the relative importance of each type of asset in each industry. We judge the relative importance of the different types of assets in each industry by using Bureau of Economic Analysis data on the 1982 Distribution of New Structures and Equipment to using industries. The required payment to capital is finally calculated as RP_kK where P_kK is the current-dollar value of the industry's stock of capital[18]. Given that the Database only reports wage and salary costs of labor, we follow Bils and Chang (1999) and magnify both production and non-production labor costs to account for employer pension payments and compensation benefits. This data is again based on information available in the underlying NIPA tables at the 2-digit level of disaggregation. In addition, we magnify total labor costs (for both production and non-production workers)

[16]Our results are robust however to an alternative specification in which factor shares vary over time and are equal to average shares in adjacent periods.

[17]See Hall and Jorgenson (1967).

[18]We also follow Bils and Chang (1999) and, given the low level of profits in manufacturing, calculate capital's share residually, assuming that the shares of all inputs sum to one. Results are robust to this alternative assumption.

by 9% to account for the database's exclusion of payments to auxiliary and support personnel. Bartelsman and Gray (1996) report that these costs account for 7.9% and 10.7% of total payroll in manufacturing in 1972 and 1986 respectively.

OLS estimates of (10) are likely to be biased because of the correlation between technology shocks and input choices. We therefore instrument the right-hand side variables using current and one period lags of deflated oil price changes, changes in government spending, changes in the US effective nominal exchange rate and monetary policy shocks estimated using a 7-variable VAR according to the Christiano, Eichenbaum and Evans (1999) block-recursive identification procedure[19]. Our instruments are similar to those used by Basu and Kimball (1997), to which we add a measure of changes in nominal exchange rates of US against its trading partners. Given the exchange rate disconnect puzzle documented in open-economy macroeconomics[20], it is unlikely that sectoral technology shocks are correlated with this variable[21].

The relatively short span of time-series observations renders industry by industry estimates of the coefficients in (10) rather imprecise. We therefore pool 2-digit industries together and estimate (10) using a panel (fixed-effects) 2SLS estimator for each SIC 2 industry[22].

C. Relationship with other evidence

In this subsection we briefly discuss our measure of sectoral technology shocks and relate our results to those in earlier work. In Table 1 we report the time-series standard deviation (averaged across all sectors) of two measures of technology shocks. The first measure we report is the change in the TFP series reported in the NBER Productivity database. This TFP measure assumes perfect competition and constant returns to scale and simply subtracts the share-weighted sum of the growth rates of inputs from the growth rate of real output. The other measure are the purified Solow residuals whose construction is discussed above: $\varepsilon_{it} = \tilde{\varepsilon}_{it} + c_i$. Note that technology shocks are very volatile at this level of disaggregation, with a standard deviation of 0.076 for the traditional Solow residuals and 0.063 for the technology shocks purified of imperfect

[19] We measure the stance of monetary policy by the size of non-borrowed reserves and assume that the Fed's information set includes current and four lagged values of real GDP, CPI, an index of commodity prices, as well as four lags of the Federal funds rate, total reserves, non-borrowed reserves and the M1 money stock. Monetary policy shocks are estimated using quarterly data. Our measure of annual shocks is the sum of four quarterly shocks.

[20] e.g, Obstfeld and Rogoff (1996)

[21] Our results are robust to excluding nominal exchange rate variables as an instrument for input growth.

[22] Our results are robust however to estimating technology shocks using separate industry-by-industry regressions.

competition, increasing returns and variable input utilization. In contrast, Basu and Fernald (2000) estimate that technology shocks in the entire manufacturing sector are almost twice less volatile: the standard deviation of the Solow residual is 0.035 and that of the purified series is 0.028 according to their estimates.

In Table 2 we compare our estimates of decreasing returns to scale implied by our estimates of (10) to those in Basu, Fernald and Kimball (2004) who use the Jorgenson dataset of 29 industries (including 21 industries at (roughly) the SIC 2 level) from 1949 to 1996[23]. Their estimation strategy differs slightly from ours as they restrict the coefficient on the proxy for input utilization to be constant across industries, but, despite the differences in the level of aggregation underlying the two sets of estimates, our results and theirs are not too dissimilar. For durable goods, the median returns to scale estimate is 1.11, compared to 1.07 in their work, with a correlation of 0.71 across coefficient estimates in the different industries. Our results differ somewhat for non-durable goods, but the low correlation between the two sets of estimates (0.41) is misleading as it is driven by two estimates of returns to scale that are insignificant (0.32 for Food in our sample and 0.11 for Leather in their work). The correlation between these elasticities for all other non-durable sectors is much higher, around 0.77. There is a significant difference between the median degree of returns to scale in our work: 1.07 and theirs: 0.89 for non-durable firms[24], but our results are in the range of those obtained using other sets of data or instrument sets[25].

4. Testing the State-Dependent Pricing Model

A. Empirical Results

Before we discuss our empirical approach, we first use our estimates of technology shocks $\varepsilon_{it} = \tilde{\varepsilon}_{it} + c_i$ constructed above[26], to estimate

[23]BFK(2004) estimate elasticities separately for SIC 371 and all other SIC 37 sectors. We calculate a weighted average of their two estimates for the SIC37 division: Transportation Equipment.

[24]Conley and Dupor (1999) find similar return to scale estimates to those in BFK (2004) (1.06 for durables and 0.91 for non-durables) using a spatial GMM estimator that models the covariance of technology shocks across industries non-parametrically as a function of economic distances for SIC 2 manufacturing industries using a set of instrument similar to ours.

[25]eg., Burnside, Eichenbaum and Rebelo (1995) find returns to scale in non-durable manufacturing equal to 1.13

[26]Throughout this paper, our definition of a sector's technology shock is the sum of the "purified Solow" residuals in equation (10) plus the fixed-effect term that captures the long-run rate of growth of an industry's technology. We choose this definition because in the model, both expected and unexpected changes in an industry's technology level affect the firms' desired prices and their responsiveness to shocks. It turns our however that variability in the fixed effect terms (c_i) is much smaller than period-by-period shocks to a sector's technology level ($\tilde{\varepsilon}_{it}$). All our results therefore change little if we use the residuals themselves as a measure of technology shocks.

$$\pi_{it} = \gamma_t^N \varepsilon_{it} \mathcal{I}_{\varepsilon_{it}<0} + \gamma_t^p \varepsilon_{it} \mathcal{I}_{\varepsilon_{it}>0} + u_{it} \tag{11}$$

for each time-period using ordinary least squares, where π_{it} are sectoral inflation rates. On average, the elasticities on negative and positive shocks are equal to each other over time (-.30 for negative, and -.31 for positive shocks), but vary substantially across periods. In Figure 6 we present a scatter plot of the difference in elasticities $\gamma_t^P - \gamma_t^N$ against shocks to aggregate inflation, measured by the change in the CPI inflation rate $\Delta\pi_t$ (left panel) as well as against changes in a measure of commodity prices[27]. Consistent with the implications of the state-dependent pricing model, periods in which aggregate shocks increase the average firm's desired prices, either because of shocks to inflation or to commodity prices, are periods in which $\gamma_t^P - \gamma_t^N$ is larger ($\left|\gamma_t^P\right| - \left|\gamma_t^N\right|$ is smaller), i.e., the responsiveness of sectoral inflation rates to technology shocks is larger in sectors in which the shocks are negative. Unless there are non-linearities in the adjusting firm's optimal pricing functions (in Section 2 we have shown that this is not the case) that cause firms to respond stronger to negative technology shocks in times of higher inflation, these figures are evidence that firms that adjust in times of higher than average inflation are more likely to be firms that experience negative technology shocks. This in turn suggests that a given firm's decision to adjust is state-dependent.

Note that we use changes in economy-wide CPI inflation, $\Delta\pi_t$, as opposed to the level of inflation as a measure of nominal disturbances. We do so because several structural breaks characterize the process for the US inflation rate over the sample considered in our empirical work. Structural breaks can affect our results for two reasons. First, firms are more likely to adjust prices in high-inflation environments, as in the 1970s and 1980s: the fraction of adjusting firms can increase in all sectors of the economy, regardless of the sector's technology disturbance. Second, structural breaks affect the firm's pricing functions and their inaction regions. For example, in periods of high inflation firms front-load and over-adjust prices in anticipation of expected future increases in the general price level. Moreover, they are more willing to tolerate prices that are above the optimum, as a rise in the aggregate price level is expected to erode the firm's real price in the future. If a structural break occurs, and inflation rates fall to a lower level, albeit a positive one, some firms would find themselves with prices that are too high, relative to what is optimal and acceptable in the

[27] We use the Commodity Research Bureau Spot Index. The data is available online at http://www.crbtrader.com/crbindex/charts.xls

new environment, and would find it optimal to lower prices, and do so more readily if subject to a favorable technology shock[28]. We will show below, that although weaker, results of our empirical work are consistent with the predictions of the state-dependent model even when the level of inflation is used as a measure of nominal disturbance.

To formally test the significance of the correlation between the difference in the responsiveness of firms to negative as opposed to positive technology shocks as a function of aggregate disturbances, we assume that γ_t^N and γ_t^p are linear functions of the aggregate shock S_t :

$$\begin{aligned}\gamma_t^N &= \beta_0 + \beta_1 S_t, \\ \gamma_t^P &= \alpha_0 + \alpha_1 S_t,\end{aligned}$$

and estimate the following panel specification:

$$\pi_{it} = \xi_i + \gamma_t^P \mathcal{I}_{(\varepsilon_{it}>0)}\varepsilon_{it} + \gamma_t^N \mathcal{I}_{(\varepsilon_{it}<0)}\varepsilon_{it} + \rho S_t + u_{it},$$

which, given the parametrization of elasticities above, reduces to

$$\pi_{it} = \xi_i + \alpha_0 \mathcal{I}_{(\varepsilon_{it}>0)}\varepsilon_{it} + \alpha_1 \left(S_t \times \mathcal{I}_{(\varepsilon_{it}>0)}\right)\varepsilon_{it} + \beta_0 \mathcal{I}_{(\varepsilon_{it}<0)}\varepsilon_{it} + \beta_1 \left(S_t \times \mathcal{I}_{(\varepsilon_{it}<0)}\right)\varepsilon_{it} + \rho S_t + u_{it}. \quad (12)$$

where ξ_i are sector-specific fixed effects. Given the estimates of β_1 and α_1, as well as the variance-covariance matrix of the coefficient estimates above[29], Table 3 reports our estimates of $\alpha_1 - \beta_1$, the difference in elasticities due to a 1% aggregate disturbance for different measures of aggregate shocks.

In Table 3, columns 1 and 2, our estimates of β_1 and α_1 are based on actual and first-differenced CPI inflation. Consistent with the evidence in Figure 6, the absolute value of the coefficient on positive technology shocks decreases relative to the one on negative technology shocks in times of higher inflation (i.e., $\alpha_1 - \beta_1$ increases), suggesting that the fraction of firms who adjust in sectors hit by negative technology shocks is

[28] See Ahlin and Shintani (2004) for a formal theoretical exposition of this idea.

[29] Given the two-stage estimation procedure we employ, classical standard errors are downward biased in our example. The procedure we use to compute correct asymptotic standard errors is discussed in the appendix.

larger in these periods than the corresponding fraction in industries hit by favorable technology shocks[30].

Ball and Mankiw (1995) discuss an alternative source of asymmetries in state-dependent pricing models. They show that if the distribution of all the firms' desired prices is, say, positively skewed, then, if the Ss bands of price adjustment are symmetric, as in a world with no aggregate uncertainty, the fraction of firms who adjust and increase prices is greater than the fraction of firms who lower prices. Hence, even if the distribution of idiosyncratic shocks is centered at zero in all periods, shocks to the third moment of the distribution will force an asymmetric adjustment by firms to positive versus negative shocks and generate economy-wide inflation. The two types of asymmetry differ, as in our model aggregate shocks trigger movements in $\gamma_t^p - \gamma_t^N$, while in their model, exogenous shocks to $\gamma_t^p - \gamma_t^N$ affect aggregate inflation[31]. Their analysis does suggest however, that, if our measures of technology shocks are imperfect, and correlated with, say, changes in energy prices that affect some sectors at the expense of others, or if the skewness of the distribution of technology shocks changes over time[32], then $\gamma_t^p - \gamma_t^N$ movements induced by these changes will on their own generate economy-wide inflation. In other words, our estimates of β and α could be biased because of endogeneity. To distinguish between these two sources of asymmetry, we next look at alternative measures of shocks to all firm's desired prices, namely, exogenous monetary policy shocks and changes in commodity prices.

The third column of Table 3 relates the difference in elasticities to changes in commodity prices. Support for the state-dependent pricing model is strong with this measure of aggregate shocks as well. The coefficient estimate of the effect of an increase in commodity price inflation on the difference in elasticities is equal to 2.5 with a t-statistic well in excess of 10.

Columns 4-6 of Table 3 asks whether monetary policy shocks affect the responsiveness of firm prices to negative, as opposed to positive idiosyncratic technology shocks. The lag with which shocks to monetary policy affect variables in the US economy prompts us to relate the difference in elasticities to current but also

[30]We report the effect of aggregate shocks on the difference in elasticities, as opposed to elasticities themselves in order to save space, but also to control for changes in the fraction of all adjusting firms, say due to synchronization, in periods with greater economy-wide disturbances. The distinction turns out to play little role. For most measures of aggregate disturbances we use, β_1 are negative and α_1 are positive, and highly significant. The only exception arises in the case of aggregate inflation, π_t,: α_1 is negative (although smaller than β_1 in absolute value), contrary to what the model predicts, suggesting that in periods of higher aggregate inflation the fraction of firms that adjusts increases in all sectors, although much more so in sectors with negative technology shocks, as predicted by the state-dependent model.

[31]Similarly, exogenous increases in the volatility of sectoral shocks will generate aggregate inflation in a model with constant trend money growth, as in Ball and Mankiw (1994).

[32]Although, including the skeweness of technology shocks in each period as an additional right-hand side variables does not alter our results.

several lags of past monetary shocks. We use three measures of shifts in the stance of monetary policy. Our first measure of shocks is estimated using the Christiano, Eichenbaum and Evans (1999) recursive identification assumption, with non-borrowed reserves as the postulated instrument. A second measure we use are the dates identified by Romer and Romer (1994) using the narrative approach, dates on which the Fed announced an intent to reduce inflation by pursuing a contractionary monetary policy[33]. Although this measure does not constitute an exogenous shift in monetary policy, it represents a measure of aggregate disturbances that do not arise due to shifts in the responsiveness of firms to positive as opposed to negative technology shocks. Our third measure of shocks is due to Romer and Romer (2004). To arrive at a measure of exogenous shifts in monetary policy, Romer and Romer (2004) first construct a series of intended changes in the federal funds target rate around the FOMC meetings using both the narrative approach as well as information on the Federal Fund's expected rate based on internal Fed memos. This series of intended policy actions is then purged of changes that arise in response to anticipated macroeconomic conditions by regressing it against "Greenbook" forecasts of future inflation, real output growth and the unemployment rate.

As the lower panel of Table 3 indicate, results based on the alternative measures of monetary disturbances are remarkably robust. Consistent with the evidence documented in earlier work, monetary policy shocks affect inflation rates only with a lag. The effect of an expansionary shock in the first year is to decrease the willingness of firms to respond to negative technology shock, a result inconsistent with the predictions of the model and related to the "price puzzle" documented in earlier work. The response of elasticities to lags of monetary policy shocks is however in line with the predictions of the model: following a lag, monetary policy shocks increase the willingness of firms to increase prices, but do so asymmetrically: firms in sectors with negative technology shocks adjust more readily. The maximal impact of the monetary shocks occurs with a lag of two/three years and is significantly different from zero (t-ratios are in excess of 5) in all cases.

We have established above the statistical significance of state-dependent pricing terms in explaining fluctuations in sectoral inflation rates. We next ask whether their effect is economically significant as well. We use our estimates of equation (12) and calculate, in Table 4, the effect of a one standard deviation

[33] Five Romer-Romer dates lie in the period we consider: 68/12, 74/04, 78/08, 79/09, 88/12. Given that our data is yearly, our measure of shocks are dummies for 69,74,79,80,89.

nominal disturbance on the elasticity of sectoral inflation to negative/positive technology shocks. We first calculate what the elasticities γ_t^N and γ_t^P would be in the absence of economy-wide disturbances, when the aggregate variables are at their time-series means: these are the estimates of $\alpha_0 + \alpha_1\mu(S)$ and $\beta_0 + \beta_1\mu(S)$ in equation (12), where $\mu(S)$ is the time-series mean of S. The four different sets of estimates in Table 4 correspond to different specifications of the aggregate disturbance in Table 3. Note first that on average firms are more willing to increase prices in response to adverse technology disturbances than lower prices in response to favorable shocks: the elasticity on positive shocks is close to -0.2, while that on negative shocks is close to -0.4 when the aggregate variables are at their steady-state means. We thus corroborate, although in a different environment, the results of Peltzman (2000) who finds that output prices are more likely to respond to cost increases, rather than decreases. We next compute the effect of a one standard deviation aggregate shock on the elasticities γ_t^N and γ_t^P (e.g., $\alpha_0 + \alpha_1 \times [\mu(S) + \sigma(S)]$), where σ is the standard deviation of the aggregate disturbance, S). Notice that for all measures of aggregate disturbances, with the exception of CPI inflation rates, an increase in the size of the nominal disturbances reduces the elasticity of sectoral inflation to positive technology shocks by around 40% (e.g., from -0.21 to -0.12 for changes in CPI inflation), while increasing that on negative technology shocks by 30% (e.g., from -0.42 to -.55 for changes in CPI inflation). An increase in the inflation rate itself increases the responsiveness to technology shocks of all sectors in the economy, although much stronger for sectors with negative technology shocks, as predicted by the model.

How important are these changes in elasticities quantitatively? To answer this question, we resort to the following experiment. Note in equation 12 that the response of sectoral inflation rates to an aggregate shock is $\frac{\partial \pi_{it}}{\partial S_t} = \rho + \alpha_1 \varepsilon_{it}$ if $\varepsilon_{it} > 0$ and $\frac{\partial \pi_{it}}{\partial S_t} = \rho + \beta_1 \varepsilon_{it}$ if $\varepsilon_{it} < 0$. We compute these derivatives for all periods/sectors in our sample for the Christiano, Eichenbaum and Evans (1999) measure of monetary policy shocks, and average them across periods/sectors for a measure of how the aggregate manufacturing industry responds to an expansionary nominal disturbance. We also calculate what these "impulse responses" would be in the absence of state-dependent terms by imposing $\alpha_1 = \beta_1 = 0$. As the table below[34] indicates, state-dependent terms increase the responsiveness of inflation rates to monetary shocks by almost 50% in the second and third year following a shock, suggesting that endogenous variation in the identity and fraction

[34]Standard errors are reported in parantheses.

of adjusting firms is an important source of movements in the overall inflation rate of the US manufacturing sector.

	$\frac{\partial \pi_t}{\partial s_t}$	$\frac{\partial \pi_t}{\partial s_{t-1}}$	$\frac{\partial \pi_t}{\partial s_{t-2}}$	$\frac{\partial \pi_t}{\partial s_{t-3}}$
No SDP terms	0.008 (0.012)	0.058 (0.013)	0.148 (0.013)	0.167 (0.012)
With SDP terms	-0.014 (0.009)	0.091 (0.016)	0.222 (0.016)	0.173 (0.016)

B. Robustness Checks

We have performed several checks to ensure the robustness of our results.

Continuous parametrization of non-linearities

We first ask whether we can find evidence of non-linearities in the sectoral inflation rates response to aggregate and sectoral shocks using a continuous parametrization of a sector's responsiveness to technology shocks. To this end, we estimate (see the justification for this parametrization in Section 2)

$$\pi_{it} = \gamma_0 + \gamma_1 \varepsilon_{it} + \gamma_2 \left(\varepsilon_{it}^2 \times g_t \right) + \gamma_3 g_t + u_{it}, \tag{13}$$

where the state-dependent model predicts that $\gamma_2 > 0$. We again find considerable support for the model, for all measures of nominal disturbances. As Table 5 indicates, coefficient estimates of γ_2 are positive, and significantly estimated (t-ratios are in excess of 5) for inflation, changes in inflation, as well as commodity price changes. Moreover, after a one-year lag, expansionary monetary policy shocks also cause a larger responsiveness to technology shocks in sectors that are hit by more negative technological disturbances.

Technology shocks estimated using long-run identification restrictions

We have redone all our work using an alternative measure of technology shocks, one based on long-run identification restrictions, in the spirit of Blanchard and Quah (1989) and Gali (1999). Specifications in which labor hours enter in levels, but also in differences produce similar results to those reported above. Results are available from the author upon request.

Time Aggregation

An additional concern is the time-aggregation of the data we use to test the state-dependent pricing model. It can be shown that the state-dependent pricing model still predicts a non-linear relationship between sectoral inflation rates and aggregate and sectoral shocks, even if the data used to estimate these non-linearities is sampled less frequently than the frequency with which prices change in the model. The importance of non-linearities falls as the degree of time-aggregation increases, which suggests that our results provide a lower bound of the quantitative importance of state-dependent pricing rules in the data.

Counter-cyclical markups

The model of Rotemberg and Saloner (1986) predicts that periods of higher demand are periods in which colluding firms are likely to behave more competitively. An extension of their model to incorporate sectoral shocks would imply that markups fall during booms, and more so for firms in sectors with positive technology shocks. Our finding above that the elasticity in response to negative technology shocks rises during periods of economy-wide disturbances can then be driven by industrial organization considerations, rather than costs of price adjustment. We tested this hypothesis by asking whether the asymmetry we find in our estimates of equation (12) is robust to including a measure of the degree of market concentration in the industries we study. Let HH_i be the Herfindhal-Herschmann index, available for four-digit industries from the Census Bureau[35]. We allow the responsiveness of sectoral inflation rates to depend on both the size of aggregate disturbances, but also the degree of the industry's market concentration:

$$\begin{aligned} \gamma_t^N &= \beta_0 + \beta_1 S_t + \beta_2 (HH \times S_t), \text{ and} \\ \gamma_t^P &= \alpha_0 + \alpha_1 S_t + \alpha_2 (HH \times S_t), \end{aligned}$$

[35]For each industry we calculate the average of the index over three years for which data is available: 1982, 1987 and 1992.

and estimate the following equation:

$$\pi_{it} = \xi_i + \alpha_0 \varepsilon_{it}^{+} + \alpha_1 \left(S_t \times \varepsilon_{it}^{+}\right) + \alpha_2 \left(HH_i \times S_t \times \varepsilon_{it}^{+}\right) + \beta_0 \varepsilon_{it}^{-} + \beta_1 \left(S_t \times \varepsilon_{it}^{-}\right) + \beta_2 \left(HH_i \times S_t \times \varepsilon_{it}^{-}\right) + \rho S_t + u_{it}. \tag{14}$$

If the results reported in the previous section are solely driven by the inability of oligopolistically competitive firms to collude in booming periods, we should observe no asymmetries in industries with a large number of small firms,where HH is close to 0, and large asymmetries in industries with a few dominant firms and a high HH index. In Table 6 we report $\alpha_1 - \beta_1$, i.e., the difference in elasticities to positive and negative technology shocks for sectors with a zero concentration ratio. Our results are similar to those reported earlier and we once again strongly reject the null of time-dependent pricing[36].

Sectoral Heterogeneity

As Bils and Klenow (2004) have documented, there is a large dispersion in the frequency of price changes in the US economy. Differences in the frequency of price changes, as well as other sources of heterogeneity (e.g., variability of shocks) will lead to differences in the responsiveness of sectoral inflation rates to sectoral and aggregate disturbances. One additional concern is therefore that the non-linearities identified above are spurious, and simply reflect the fact that we do not allow for a differential response to sectoral and aggregate shocks across sectors. We address this concern by allowing the elasticities to technology shocks, as well as aggregate disturbances, to differ across the 446 4-digit sectors in our analysis. We estimate

$$\pi_{it} = \xi_i + \sum_{i=1}^{446} \gamma_i \varepsilon_{it} D_i + \sum_{i=1}^{446} \rho_i S_t D_i + \beta_0 \varepsilon_{it} \mathcal{I}_{(\varepsilon_{it}>0)} + \alpha_1 \left(S_t \times \mathcal{I}_{(\varepsilon_{it}>0)}\right) \varepsilon_{it} + \beta_1 \left(S_t \times \mathcal{I}_{(\varepsilon_{it}<0)}\right) \varepsilon_{it} + u_{it} \tag{15}$$

where D_i is a dummy for each SIC-4 sector, and report the results in Table 7. Note that heterogeneity across sectors is indeed responsible for some of the non-linearities we have found above in the responsiveness of sectoral inflation rates to nominal disturbances: the coefficient estimates of $\alpha_1 - \beta_1$ decline by almost two-thirds when changes in inflation and commodity price changes are used as a measure of aggregate shocks

[36]We only report results based on three measures of nominal disturbances: CPI inflation, commodity price inflation, as well as changes in CPI inflation for this and the subsequent robustness checks in order to conserve space.

(although they decrease by much less when CPI inflation itself is employed). The statistical significance of these estimates is not affected, and we again find significant non-linearities in the data, non-linearities that cannot arise in time-dependent models.

Sub-sample Stability

We finally ask whether our results are robust across sub-samples, and in particular, before and after the Volcker disinflation. We estimate equation (12) separately, using observations for the years 1961-1981 and 1982-1996. As Table 8 indicates, results are robust across sub-samples, although, not surprisingly, non-linearities are easier to identify during the pre-Volcker era of higher and more volatile inflation rates.

5. Conclusion

If pricing is state-dependent, firms are more likely to pay the adjustment costs and change prices if idiosyncratic and aggregate shocks reinforce each other and trigger desired price changes in the same direction. The state-dependent model therefore predicts that the distribution of idiosyncratic shocks, conditional on adjustment, varies endogenously in response to aggregate disturbances. This paper explores this asymmetry in order to test whether pricing in the US economy is state or time-dependent. Using highly disaggregated four-digit data on sectoral input, output and inflation rates in the US manufacturing sector, we find that sectors that are hit by negative technology shocks adjust more readily in times of greater inflation, increases in commodity prices and larger monetary policy shocks. These results suggest that the timing of firm price adjustments is indeed endogenous, as in state-dependent pricing models.

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Table 1: Two measures of technology shocks

	Standard Deviation	Correlation
NBER MP Database TFP growth	0.076	0.63
Purified Solow residuals	0.063	

Table 2: Comparison with Basu Fernald and Kimball (2004)
Degree of increasing returns

Durable

	our estimates	BFK estimates
Lumber	0.84	0.51
Furniture	1.05	0.92
Stone, Clay & Glass	1.32	1.08
Primary Metal	0.95	0.96
Fabricated Metal	1.17	1.16
Non-Electric Machinery	1.03	1.16
Electrical Machinery	1.34	1.11
Transportation Equipment	1.08	1.05
Instruments	1.15	0.95
Misc. Manufacturing	1.24	1.17
median	1.11	1.07
correlation	0.71	

Non-durable

	our estimates	BFK estimates
Food	0.46	0.84
Tobacco	0.84	0.90
Textiles	1.09	0.64
Apparel	1.07	0.70
Paper	1.02	1.02
Printing & Publishing	1.25	0.87
Chemicals	1.66	1.83
Petroleum Products	0.98	0.91
Rubber & Plastics	1.25	0.91
Leather	1.19	0.11
median	1.08	0.89
correlation	0.41	
correlation w/o outliers	0.77	

Table 3: Effect of Nominal Disturbances on the difference in (+,-) elasticities

A: Effect of Aggregate Inflation

	1	2	3
π_t	4.83		
	(0.64)		
$\Delta\pi_t$		9.85	
		(1.05)	
ΔPcom$_t$			2.46
			(0.18)
R2	0.37	0.15	0.17
# obs	16056	16056	16056

B: Effect of Monetary Policy Shocks

	4 **CEE**	5 **RR dates**	6 **RR shocks**
shock(t)	-0.94	-0.43	-0.08
	(0.37)	(0.06)	(0.03)
shock(t-1)	1.33	0.18	0.08
	(0.41)	(0.05)	(0.03)
shock(t-2)	3.30	0.33	0.15
	(0.41)	(0.06)	(0.03)
shock(t-3)	0.46	0.08	0.25
	(0.45)	(0.05)	(0.03)
R2	0.17	0.26	0.27
# obs	16056	16056	12488

Notes:

1. Fixed Effects estimates of α_1-β_1 in equation (12) reported
2. Standard errors in parantheses (corrected for bias arising from two-stage estimation)
3. In (6) we lose eight years of observations because Romer and Romer data is available from 1969
4. Coefficient estimates on Romer dates and Romer shocks (contractionary shocks) are multiplied by (-1)

Table 4: Is state-dependent pricing quantitatively important?

Elasticity of sectoral inflation to sectoral technology shocks

		$\pi_t = \mu(\pi)$	$\pi_t = \mu(\pi) + \sigma(\pi)$
(1) π_t	positive shocks	-0.245 (0.013)	-0.297 (0.016)
	negative shocks	-0.326 (0.012)	-0.525 (0.022)

		$\pi_t = \mu(\Delta\pi)$	$\pi_t = \mu(\Delta\pi) + \sigma(\Delta\pi)$
(2) $\Delta\pi_t$	positive shocks	-0.209 (0.013)	-0.118 (0.016)
	negative shocks	-0.424 (0.015)	-0.545 (0.027)

		$\pi_t = \mu(\Delta Pcom)$	$\pi_t = \mu(\Delta Pcom) + \sigma(\Delta Pcom)$
(3) $\Delta Pcom_t$	positive shocks	-0.225 (0.014)	-0.135 (0.016)
	negative shocks	-0.405 (0.015)	-0.595 (0.024)

		$\Delta shock_{t-2} = \mu(shock)$	$\Delta shock_{t-2} = \mu(shock)+\sigma(shock)$
(4) **CEE monetary shock (after a 2-year lag)**	positive shocks	-0.216 (0.013)	-0.156 (0.017)
	negative shocks	-0.418 (0.013)	-0.547 (0.023)

Note:

1 . numbers in parantheses denote the specification used to estimate elasticities and correspond to those in Table 3

2. standard errors in parantheses (these ignore uncertainty in our estimates of the mean and standard deviation of the three aggregate shocks)

Table 5: A Continuous Parametrization of responsiveness to technology shocks
Coefficient estimates of the non-linear term

A: Effect of Aggregate Inflation

	1	2	3
π_t	4.61 (0.86)		
$\Delta\pi_t$		17.62 (3.97)	
ΔPcom$_t$			4.13 (0.64)
R2	0.20	0.14	0.16
# obs	16056	16056	16056

B: Effect of Monetary Policy Shocks

	4 **CEE**	5 **RR dates**	6 **RR shocks**
shock(t)	0.69 (0.71)	-1.01 (0.18)	-0.23 (0.04)
shock(t-1)	3.73 (1.08)	0.43 (0.11)	0.32 (0.05)
shock(t-2)	6.85 (1.05)	0.45 (0.12)	0.29 (0.07)
shock(t-3)	1.31 (1.21)	-0.17 (0.09)	0.39 (0.07)
R2	0.15	0.22	0.26
# obs	16056	16056	12488

Notes:
1. Fixed Effects estimates of γ_2 in equation (13) reported
2. Standard errors in parantheses (corrected for bias arising from two-stage estimation)
3. In (6) we lose eight years of observations because Romer and Romer data is available from 1969
4. Coefficient estimates on Romer dates and Romer shocks (contractionary shocks) are multiplied by (-1)

Table 6: State-Dependent Pricing or Oligopolistic Competition?

	1	2	3
π_t	3.20		
	(0.62)		
$\Delta\pi_t$		9.76	
		(1.31)	
$\Delta Pcom_t$			2.16
			(0.23)
R2	0.37	0.15	0.17
# obs	16056	16056	16056

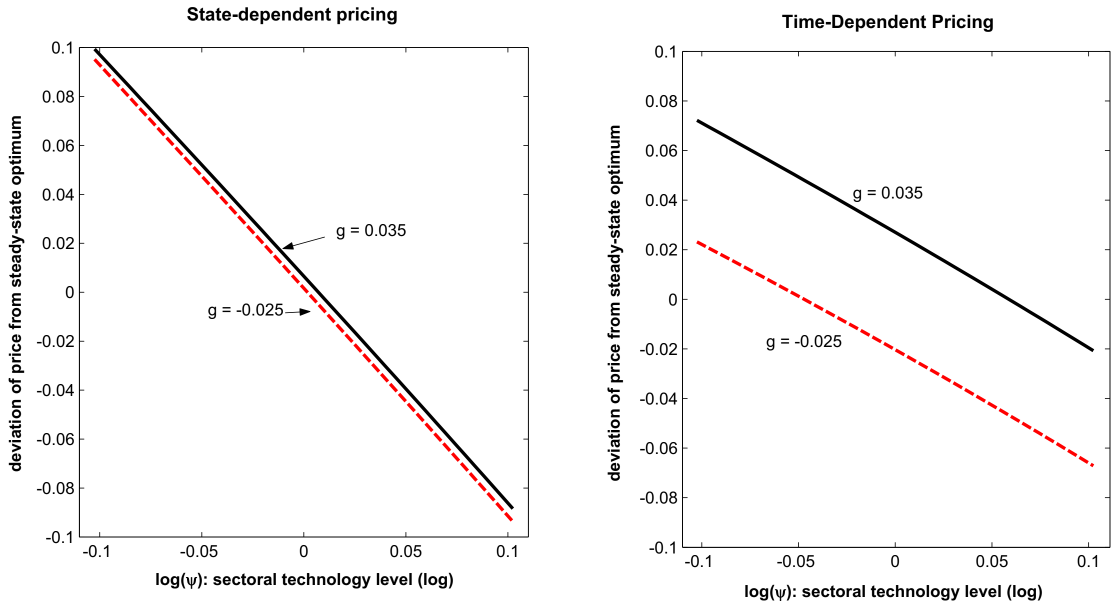
Table 7: Sectoral Heterogeneity?

	1	2	3
π_t	3.82		
	(0.39)		
$\Delta\pi_t$		3.44	
		(0.66)	
$\Delta Pcom_t$			0.74
			(0.13)
R2	0.48	0.30	0.31
# obs	16056	16056	16056

Table 8: Sub-Sample Stability?

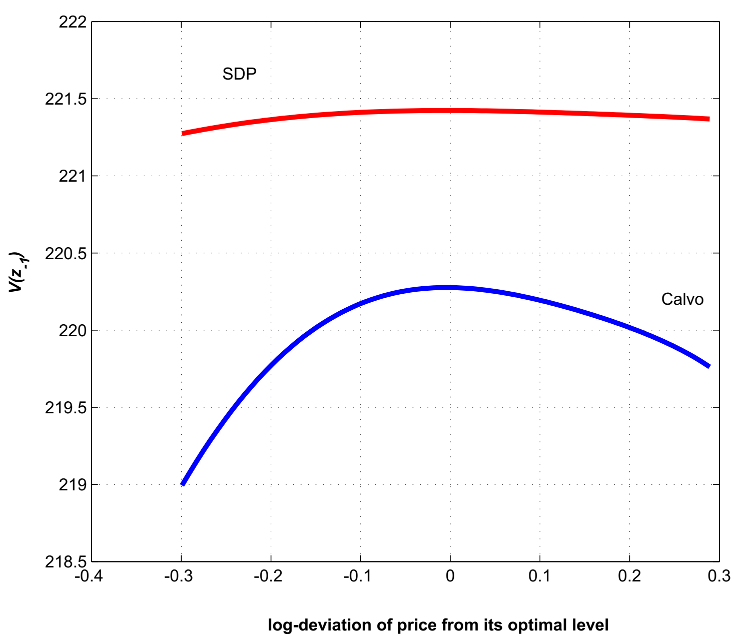
	1		2		3	
	1961-81	1982-96	1961-81	1982-96	1961-81	1982-96
π_t	4.24	0.22				
	(0.39)	(1.95)				
$\Delta\pi_t$			10.58	4.58		
			(1.34)	(1.25)		
$\Delta Pcom_t$					2.36	1.46
					(0.22)	(0.28)
R2	0.42	0.11	0.19	0.09	0.21	0.11
# obs	9366	6690	9366	6690	9366	6690

Figure 1: Price Functions Conditional on Adjustment



Note: idiosyncratic technology set at steady-state-level

Figure 2: Value of Inaction in State and Time-Dependent Pricing Models



Note: all other arguments set at steady-state levels

Figure 3: Fraction of adjusters in a sector: Fr(ε, g)

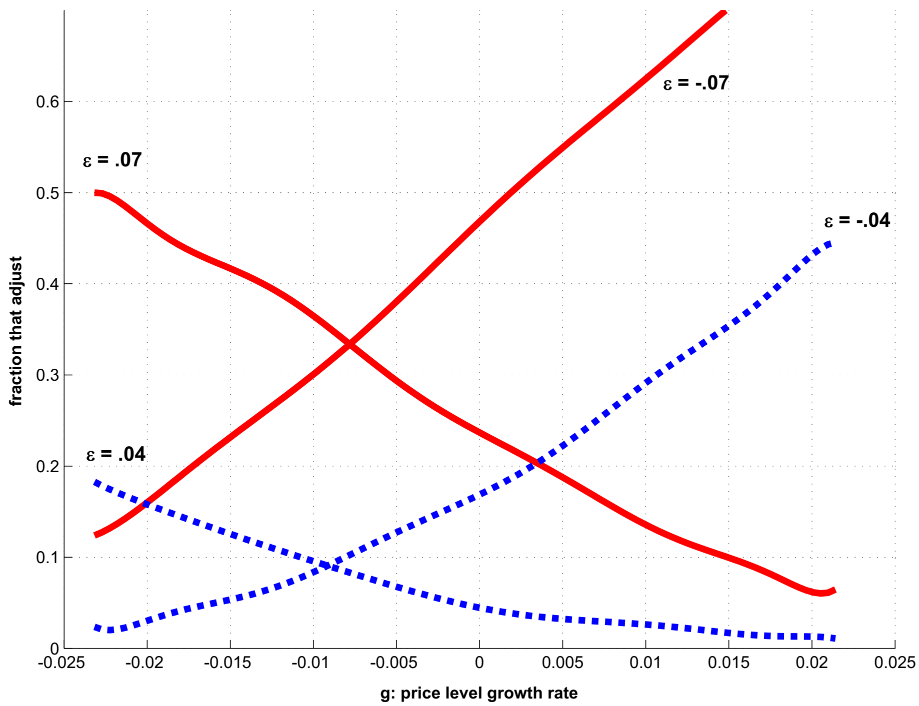
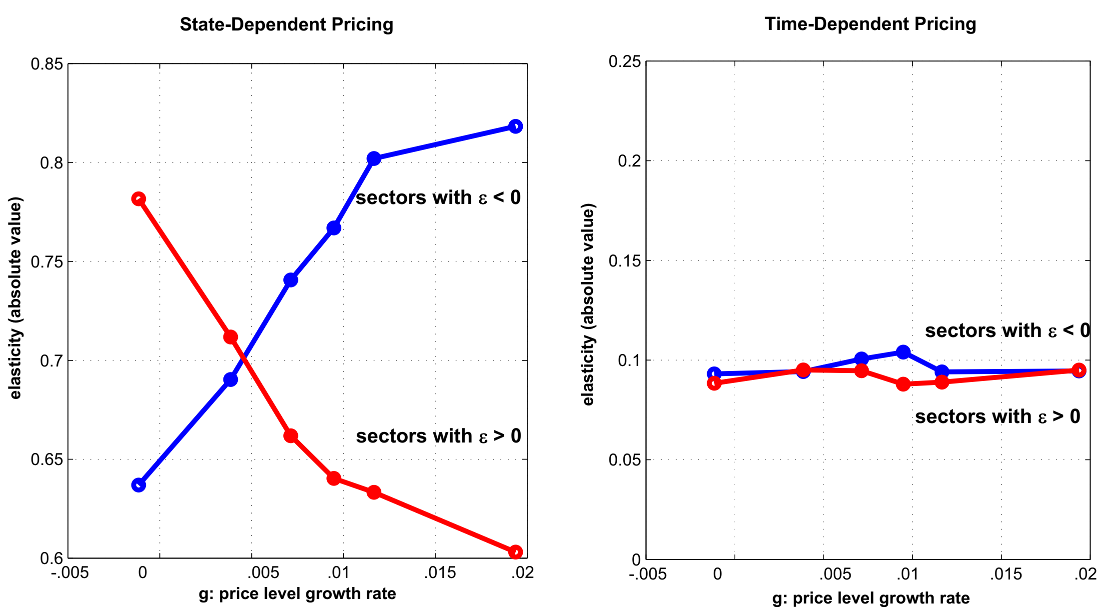


Figure 4: Responsiveness to technology shocks



Note: the two figures are scaled so that the slopes of the curves in the different figures can be directly compared

Figure 5: Effect of Aggregate Shocks on the Difference in (+,-) elasticities:
Model Simulations

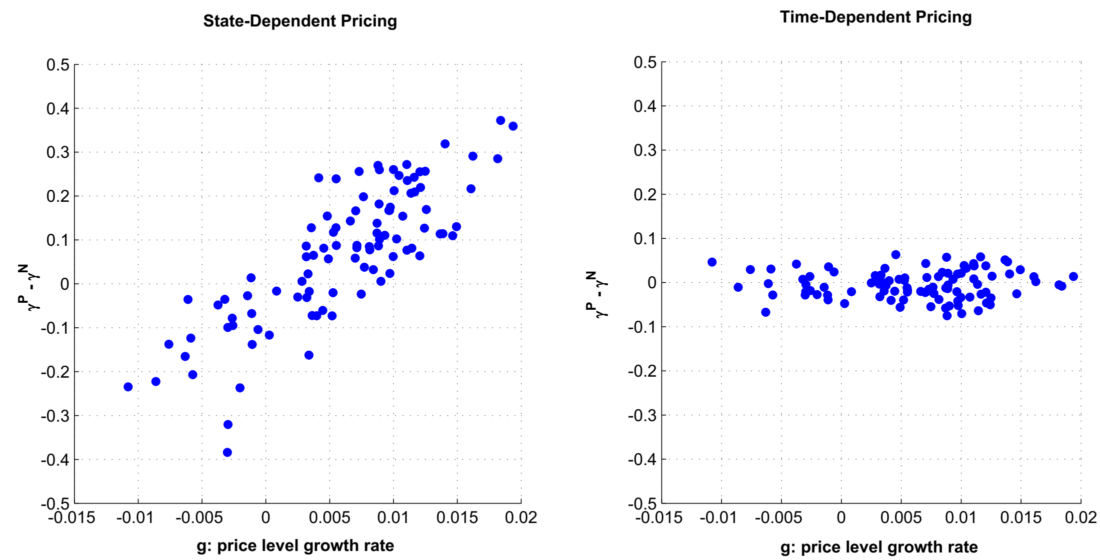
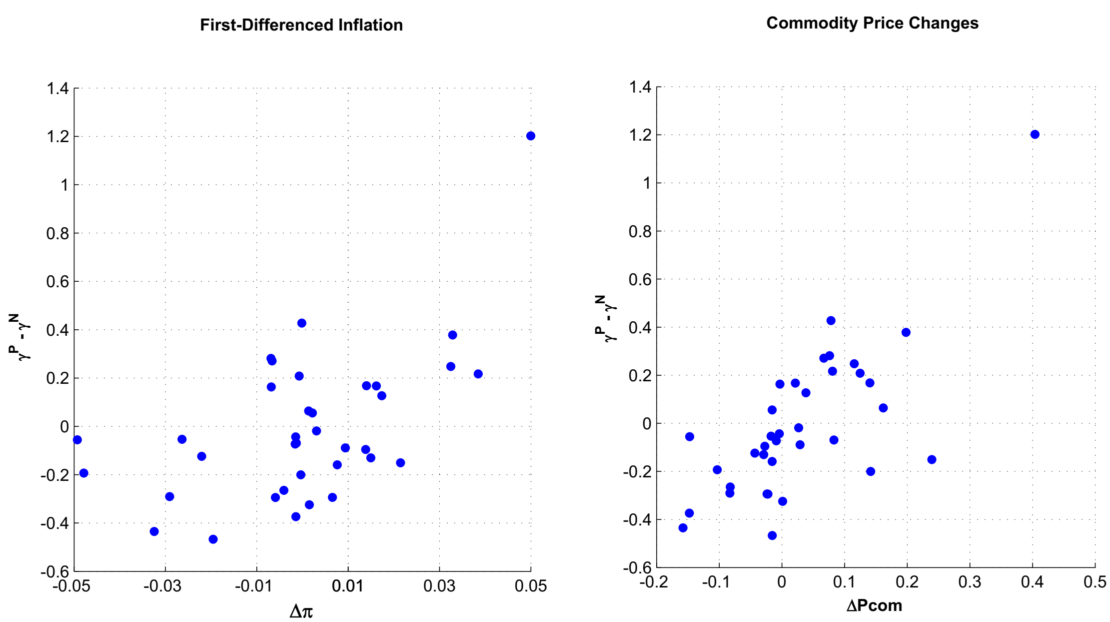


Figure 6: Effect of Aggregate Shocks on the Difference in (+,-) Elasticities:
US Manufacturing: 1961-1996



Appendix 1: Solving the State-Dependent Model

Recall that the firm's problem is:

$$V^a(s) = \max_z \left[z^{-\theta}\left(z - \frac{c}{\psi\phi}\right) + \beta \int\limits_{\varepsilon\times u\times\eta} V\left(s'\left(z, s, \varepsilon, u, \eta\right)\right) dF(\varepsilon, u, \eta) \right],$$

$$V^n(s) = \left[\left(\frac{z_{-1}}{e^g}\right)^{-\theta}\left(\frac{z_{-1}}{e^g} - \frac{c}{\psi\phi}\right) + \beta \int\limits_{\varepsilon\times u\times\eta} V\left(s'\left(\frac{z_{-1}}{e^g}, s, \varepsilon, u, \eta\right)\right) dF(\varepsilon, u, \eta) \right],$$

where $V = \max(\, V^a(s), V^n(s))$, and $s = (z_{-1}, \psi, \phi, g)$. We solve this problem numerically, using collocation.[1] We approximate the two value functions using linear combinations of Chebyshev polynomials:, e.g.,

$$V^a(s) \approx \sum_{i_1=1}^{N_1}\sum_{i_2=1}^{N_2}\sum_{i_3=1}^{N_3}\sum_{i_4=1}^{N_4} c_{i_1 i_2 i_3 i_4}\phi_{i_1}(z_{-1})\phi_{i_2}(\psi)\phi_{i3}(\phi)\phi_{i4}(g),$$

where $\phi_{i_j}()$ is an i_j-th degree Chebyshev polynomial evaluated at the respective argument, N_j is the degree of the approximation along each dimension, and $c_{i_1 i_2 i_3 i_4}$ the unknown coefficients. This approximation reduces the infinite-dimensional problem of solving the system of two functional equations above to a finite-dimensional non-linear system of $2N_1N_2N_3N_4$ equations in the unknown coefficients $c_{i_1 i_2 i_3 i_4}$. The equations we use to solve for these unknown coefficients arise from the condition that the system of equations above holds exactly at $N_1N_2N_3N_4$ nodes along the state-space. A Newton routine is used to solve for the unknown coefficients, as well as to solve the maximization problem in the right hand-side of the first equation. We use Gaussian quadrature to form expectations (evaluate the integrals). The essence of this approach is to replace the joint-distribution of technology and monetary shocks using a discrete distribution with K mass points. The weights and nodes of the discrete distribution are chosen to ensure that the first $2K$ moments of the original distribution are equal to those of the approximant[2].

The upper panel of Figure A1 plots the price function in the (z_{-1}, g) as well as (z_{-1}, a) directions, where

[1] This solution method is extensively discussed in Miranda and Fackler (2002).
[2] See again Miranda and Fackler (2002).

$a = \psi\phi$ is the firm's technology. Note the region of inaction in which the firm's nominal price is unchanged (the center of the two figures), as well as the region in which the firm changes its price. The lower panel of the figure plots the firm's value of not changing its price in the (z_{-1}, g) space. The firm's value declines as g moves away from 0 and z_{-1} away from 1. Finally, the lower-right panel of this figure plots the firm's value (the maximum of the value of adjustment and non-adjustment) and once again illustrates the region of inaction in which the firm exercises the option to not change its nominal price.

We gauge the accuracy of the approximants we use by calculating the difference between the right and left-hand side of the Bellman equations at points other than the nodes used to solve for the unknown coefficients. The maximum difference is small in absolute value (less than $.5\times10^{-4}$), suggesting the accuracy of the solution method.

Appendix 2: Standard Errors for Two-Stage Estimates

We test the implication of state-dependent pricing models in two stages with residuals estimated in the first stage used as a dependent variable in the second-stage estimation. This appendix discusses how we calculate asymptotic standard errors for our second-stage estimates that take into account the two-stage nature of our estimation.

In stage 1, we rely on two-stage least squares regressions in which we retrieve residuals (technology shocks) to be used in the second stage estimation. For each SIC 2-digit industry, we estimate technology shocks as the residuals from the following Fixed Effects 2SLS regressions. Letting Δy_{it} be the growth rate of log output of industry i, c_i be industry-specific effects and $g'_{it} = [\Delta x_{it}, \Delta h_{it}]$ be the regressors (share-weighted growth rate of primary inputs), we estimate:

$$\Delta y_{it} = g'_{it}\alpha + c_i + \tilde{\varepsilon}_{it}$$

Let ξ_{it} be the instruments we use for g and rewrite the above expression more compactly as

$$Y = G\alpha + (I_N \otimes \iota_T)\, c + \varepsilon$$

where $G' = [g_{11}, ...g_{1T}, ..., g_{N1}, ..., g_{NT}], Y' = [\Delta y_{11}, ..\Delta y_{1T}, ..., \Delta y_{N1}, ..., \Delta y_{NT}], c = [c_1, ..., c_N]\,, I_N$ is the identity matrix, and ι_T is a T×1 vector of ones. The Fixed-effects two stage least squares estimate of α is

$$\hat{\alpha} = \left(\tilde{G}P_{\xi}\tilde{G}\right)^{-1}\tilde{G}P_{\xi}\tilde{Y}$$

where $\tilde{G} = QG, \tilde{Y} = Qy$, Q is the matrix that demeans observations of sector-specific time-series means, and $P_{\xi} = \tilde{\xi}\left(\tilde{\xi}'\tilde{\xi}\right)\tilde{\xi}'$,with $\tilde{\xi}$ denoting the demeaned $NT \times j$ matrix of stacked instruments. We consider asymptotic results for the case $N \longrightarrow \infty$, holding constant T. Under standard regularity conditions:

$$\sqrt{N}\left(\hat{\alpha} - \alpha\right) = \left(\frac{1}{N}\tilde{G}P_{\xi}\tilde{G}\right)^{-1}\frac{1}{\sqrt{N}}\tilde{G}P_{\xi}\varepsilon \stackrel{d}{\longrightarrow} N\left(0, V_1\right)$$

Assuming that technology shocks are serially and cross-sectionally independent and homoskedastic, we estimate V_1 using

$$\hat{V}_1 = \hat{\sigma}^2\left(\frac{1}{N}\tilde{G}P_{\xi}\tilde{G}\right)^{-1}, \text{where } \sigma^2 = \frac{1}{N(T-1)}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{\varepsilon}_{it}^2$$

The technology shocks are therefore $\varepsilon_{it} = \hat{\varepsilon}_{it} + \bar{y}_i - \bar{g}_i'\hat{\alpha}$, where $\hat{\varepsilon}_{it}$ are the residuals of the regression above, and $\bar{y}_i - \bar{g}_i'\hat{\alpha}$ the estimate of the fixed effect term. In the second stage, we construct $\varepsilon_{it}^{+} = \max(\varepsilon_{it}, 0)$ and $\hat{\varepsilon}_{it}^{-} = \min(\varepsilon_{it}, 0)$ and estimate

$$\pi_{it} = \theta_i + s_t'\delta + \gamma_1\hat{\varepsilon}_{it}^{+} + \gamma_2\hat{\varepsilon}_{it}^{-} + \hat{\varepsilon}_{it}^{+}s_t'\gamma_3 + \hat{\varepsilon}_{it}^{-}s_t'\gamma_4 + u_{it}$$

where s_t are aggregate shocks and θ_i are fixed-effects. Letting $\beta = \left[\delta' \;\; \gamma_1 \;\; \gamma_2 \;\; \gamma_3' \;\; \gamma_4'\right]'$, x_{it} collect all the right-hand side covariates and a tilde denote a demeaned variable, the fixed effects estimator is the solution to:

$$\arg\min_{\beta}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\tilde{\pi}_{it} - \tilde{x}_{it}'\beta\right)^2 = \arg\max_{\beta}\sum_{i=1}^{N}\sum_{t=1}^{T}\psi\left(z_{it}, \beta, \hat{\alpha}\right)$$

where z_{it} is the data we use in both stages of the estimation procedure and $\hat{\alpha}$ are the coefficient estimates from the first-stage regressions. To calculate its asymptotic distribution we note that $\hat{\beta}$ satisfies:

$$\frac{1}{\sqrt{N}}\sum_{i=1}^{N}\sum_{t=1}^{T}\frac{\partial}{\partial\beta}\psi\left(z_{it},\hat{\beta},\hat{\alpha}\right)=0$$

A first-order Taylor series expression of this expression around θ and α yields:

$$0 \approx \tfrac{1}{\sqrt{N}}\textstyle\sum_{i=1}^{N}\sum_{t=1}^{T}\tfrac{\partial}{\partial\beta}\psi\left(z_{it},\beta,\alpha\right)+B_N\sqrt{N}\left(\hat{\beta}-\beta\right)+J_N\sqrt{N}\left(\hat{\alpha}-\alpha\right),$$

$$\text{where, } B_N=\left(\tfrac{1}{N}\textstyle\sum_{i=1}^{N}\sum_{t=1}^{T}\tfrac{\partial}{\partial\beta}\tfrac{\partial}{\partial\beta'}\psi\left(z_{it},\beta,\alpha\right)\right)\xrightarrow{p}B=E\left[\textstyle\sum_{t=1}^{T}\tfrac{\partial}{\partial\beta}\tfrac{\partial}{\partial\beta'}\psi\left(z_{it},\beta,\alpha\right)\right]$$

$$J_N=\left(\tfrac{1}{N}\textstyle\sum_{i=1}^{N}\sum_{t=1}^{T}\tfrac{\partial}{\partial\beta}\tfrac{\partial}{\partial\alpha'}\psi\left(z_{it},\beta,\alpha\right)\right)\xrightarrow{p}J=E\left[\textstyle\sum_{t=1}^{T}\tfrac{\partial}{\partial\beta}\tfrac{\partial}{\partial\alpha'}\psi\left(z_{it},\beta,\alpha\right)\right]$$

Hence,

$$\left(\tfrac{1}{N}\textstyle\sum_{i=1}^{N}\sum_{t=1}^{T}\tfrac{\partial}{\partial\beta}\tfrac{\partial}{\partial\beta'}\psi\left(z_{it},\beta,\alpha\right)\right)\sqrt{N}\left(\hat{\beta}-\beta\right)=-\left[I\quad J_N\right]\begin{bmatrix}\tfrac{1}{\sqrt{N}}\sum_{i=1}^{N}\sum_{t=1}^{T}\tfrac{\partial}{\partial\beta}\psi\left(z_{it},\beta,\alpha\right)\\ \left(\tfrac{1}{N}\tilde{G}P_\xi\tilde{G}\right)^{-1}\tfrac{1}{\sqrt{N}}\tilde{G}P_\xi\varepsilon\end{bmatrix}\xrightarrow{d}N(0,V_2)$$

$$\text{where } V_2=\lim_{T\to\infty}\left[I\quad J_T\right]E\begin{bmatrix}\tfrac{1}{\sqrt{N}}\sum_{i=1}^{N}\sum_{t=1}^{T}\tfrac{\partial}{\partial\beta}\psi\left(z_{it},\beta,\alpha\right)\\ \left(\tfrac{1}{N}\tilde{G}P_\xi\tilde{G}\right)^{-1}\tfrac{1}{\sqrt{N}}\tilde{G}P_\xi\varepsilon\end{bmatrix}\begin{bmatrix}\tfrac{1}{\sqrt{N}}\sum_{i=1}^{N}\sum_{t=1}^{T}\tfrac{\partial}{\partial\beta}\psi\left(z_{it},\beta,\alpha\right)\\ \left(\tfrac{1}{N}\tilde{G}P_\xi\tilde{G}\right)^{-1}\tfrac{1}{\sqrt{N}}\tilde{G}P_\xi\varepsilon\end{bmatrix}\begin{bmatrix}I\\ J_T'\end{bmatrix},$$

or

$$V_2=\left[I\quad J\right]\begin{bmatrix}A_{11} & A_{12}\\ A_{12} & A_{22}\end{bmatrix}'\begin{bmatrix}I\\ J'\end{bmatrix}$$

Note however that $\frac{\partial}{\partial\beta}\psi\left(z_{it},\beta,\alpha\right)$ is proportional to u_{it}, the error term in the second-stage regression, which is by assumption orthogonal to technology shocks. Therefore, $A_{12}=A_{21}=0$. A_{22} is the asymptotic variance of $\hat{\alpha}$ in the first-stage regression (V_1 above) and $V_2=B^{-1}A_{11}B^{-1}+B^{-1}JV_1J'B^{-1}$. We report $\hat{V}_2$, as opposed to $B^{-1}A_{11}B^{-1}$ in the text.

Figure A1: Price and Value functions