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A NOTE ON DEMAND AND SUPPLY FACTORS IN MANUFACTURING OUTPUT ASYMMETRIES

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In a Markov switching framework, we show that the duration of recessions is significantly shorter than the duration of expansions in 11 manufacturing sectors, and in aggregate durables and manufacturing output. We find two leading indicators, consumer expectations and the term spread, act as important demand-driven forces behind asymmetry.

Keywords: Asymmetry, Industry, Markov Switching, Leading Indicators

1. INTRODUCTION

We study the dynamics of the manufacturing component of GDP. We first document that the output growth rate for the majority of sectors and their aggregates is different (asymmetric) in recessions and expansions. Compared to expansions, recessions are deeper deviations from trend and have shorter expected duration. This finding raises a basic question that we address in this paper. Which factors of production may be responsible for the sectoral asymmetry?

We characterize asymmetry using aggregate quarterly data on sectoral output from 1967 to 1997. We estimate a sector-level Markov switching model in which transition probabilities between recession and expansion may differ. We find that unlike aggregate GDP, the majority of durable goods manufacturing sectors exhibit deep recessions.

Our main methodological contribution is augmentation of the Markov switching model to include aggregate economic factors. We examine whether the sector output asymmetry may be related to aggregate macroeconomic factors such as oil price shocks, macroeconomic leading indicators, and a measure of relative

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price changes. We demonstrate that the slope of the yield curve and consumer expectations seem to be the most important factors in manufacturing sector asymmetry. A new finding of this paper is the ability of consumer expectations to explain asymmetry in eight out of eleven sectors. Apparently, the asymmetry in many manufacturing sectors reflects the asymmetry in the dynamics of consumer expectations.

Our paper extends the existing literature in several dimensions. We present extensive empirical evidence on sectoral asymmetry and support papers that find differences in the dynamics of manufacturing sectors. Whereas Fok et al. (2005) argue for modeling sectors separately for forecasting purposes, Krolzig and Sensier (2000) detect a common cycle in U.K. manufacturing sectors. Bidarkota (1999) also questions the importance of sectoral differences in modeling the durables component of GDP. We support the finding of Rothman (2003), who finds that employment asymmetry is concentrated in durable goods manufacturing. We find asymmetry in seven out of ten durable goods manufacturing sectors and only in four out of ten nondurable goods manufacturing sectors.

We then present empirical evidence on validity of many possible explanations of sectoral asymmetry. Unlike Davis and Haltiwanger (2001), who report that the oil price shocks may be the explanation behind asymmetry, we fail to detect any significant effect of oil price changes on the dynamics of manufacturing sectors in expansions and contractions. We also do not find support for Ball and Mankiw's (1995) explanation of asymmetry. Ball and Mankiw claim that, due to adjustment costs, firms may respond to large shocks but not small ones. They suggest that measures of sectoral price dispersion may better capture asymmetric supply-side influences on the economy. We do not detect a significant effect of sectoral price dispersion on the asymmetry of sectoral recessions.

We describe the data in Section 2. The factor-augmented Markov switching model is developed in Section 3. We define and outline a test for asymmetry in this section as well. The model without factors is estimated in Section 4. Aggregate driving forces that might explain asymmetry in manufacturing are explored in Section 5. Section 6 estimates the factor augmented model. Section 7 concludes with some of the implications for business cycle modeling.

2. DATA

We collected sales and inventory data for January 1967 to December 1997 on durables and nondurables manufacturing sectors.[1] The data are in millions of chained 1996 dollars, converted to quarterly and seasonally adjusted by the Bureau of Economic Analysis.[2] In the durable goods group are (1) all durable goods; (2) lumber and wood products (SIC 24); (3) furniture and fixtures (SIC 25); (4) stone, clay, and glass (SIC 32); (5) primary metals (SIC 33); (6) fabricated metal (SIC 34); (7) industrial machinery (SIC 35); (8) electronic machinery (SIC 36); (9) transportation equipment (SIC 37); (10) instruments (SIC 38); and (11) other manufacturing durables (SIC 39).

TABLE 1. Cyclical characteristics of GDP and sectors

Sector	% Stdev.	Skewness	Output declines in: Recession	Expansion	Total	Recessions 2Q<0
GDP	0.90	−0.18	16	3	19	5
Manufacturing	2.18	−1.05	20	22	42	10
Services	0.36	−0.28	3	0	3	0
Durable goods	3.08	−0.99	18	23	41	7
Lumber	5.09	−0.24	14	40	54	13
Furniture	3.48	−0.33	19	31	50	12
Stone clay glass	3.32	−0.70	19	31	50	11
Primary metals	5.65	−0.57	18	38	56	10
Fabr. metals	3.47	−0.78	16	32	48	11
Industrial mach.	3.34	−0.77	15	19	34	6
Electronic mach.	3.23	−1.12	16	23	39	10
Transport eq.	6.39	0.01	17	36	53	14
Instruments	2.59	−0.43	12	25	37	8
Other manuf.	4.50	−0.58	15	36	51	11
Nondurable goods	1.71	−0.73	17	26	43	12
Food	2.14	0.48	12	40	52	14
Tobacco	5.75	−0.47	11	48	59	14
Textiles	3.06	−0.40	13	33	46	13
Apparel	4.08	0.08	15	44	59	17
Paper	2.22	−1.52	11	32	43	9
Printing	2.33	−1.15	17	36	53	13
Chemicals	2.84	−1.00	16	27	43	10
Petroleum	4.13	−0.63	14	45	59	16
Rubber	3.88	−0.59	13	28	41	9
Leather	5.95	0.32	16	49	65	18
Sector means	3.67	−0.57	15.4	33.2	48.6	11.7

Notes: The data is in annualized quarterly growth rates are quarterly spanning from 1967:3 to 1997:4. The output declines in columns 3 and 4 are based on NBER recessions. The last column is the number of recessions, based upon two consecutive quarterly output declines.

In the nondurables group are (1) all nondurable goods; (2) food (SIC 20); (3) textiles (SIC 22); (4) apparel (SIC 23); (5) paper (SIC 26); (6) printing (SIC 27); (7) chemicals (SIC 28); (8) petroleum and coal (SIC 29); (9) rubber and plastic (SIC 30); and (10) leather (SIC 31).

We form output series using the production identity[3]

$$Y_{n,t} = S_{n,t} + \Delta I_{n,t},$$

where Y_n is the output of sector n, S_n is sales, and I_n is inventories.[4] Some descriptive statistics and the cyclical behavior of sectoral output are contained in Table 1.

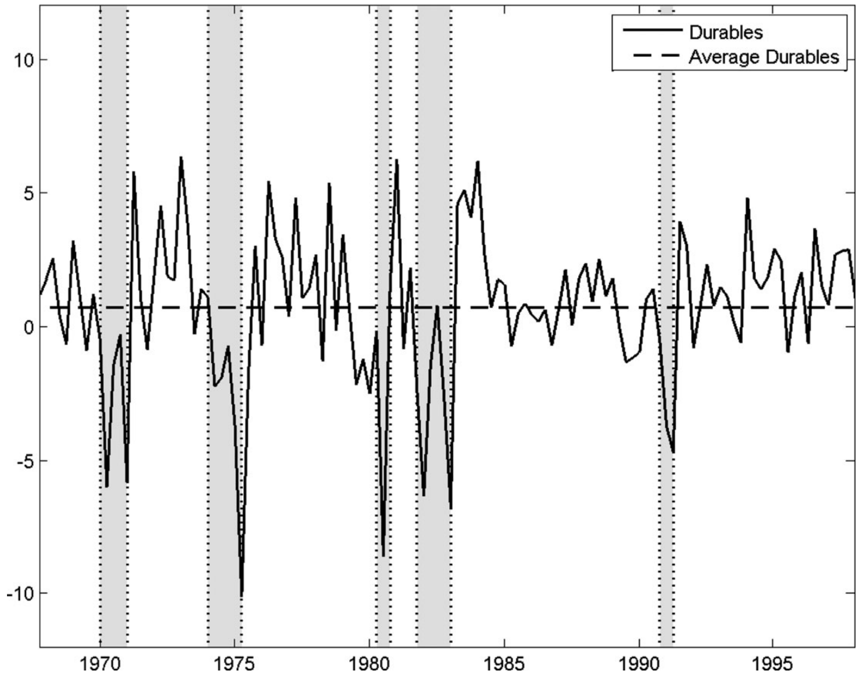

FIGURE 1. Quarterly output growth in durable goods manufacturing.
Notes: The figure plots quarterly output growth rates for durable goods manufacturing from 1967 to 1997. The shaded regions are NBER recessions.

Table 1 suggests that there are important differences in the cyclical behavior and asymmetry of GDP and disaggregated sectoral data. GDP declines are fairly rare, only 19 quarters in the 125-quarter sample. Only three of these declines occur outside of NBER recessions. Services show secular growth, with only three negative quarters in our sample. The manufacturing sectors show declines in output almost three times as often, 48.6 quarters on average. More than 68% of these declines occur outside of recessions. Assuming that two consecutive quarterly declines constitute a recession, the sectors are much more cyclical, with 11.7 "recessions" on average.

Although evidence of asymmetry for aggregate GDP and services is fairly weak, it is much stronger for manufacturing. Figure 1 shows the rapid contractions in durable goods output that contribute to asymmetry.

The 1973–1975 recession is particularly severe, with one quarterly decline approaching -10%. Even in the mild recession of 1990–1991, durable goods output falls by nearly -5%. There are also steep declines in growth outside of recessions in both the 1970s and the 1980s.

Statistical analysis confirms what we see in Figure 1. The coefficient of skewness is -0.18 for GDP and -0.28 for services, confirming both Razzak's (2001) nonparametric estimates and recent evidence from Markov switching models for aggregate output. For manufacturing, on the other hand, skewness is three times higher, -1.05. Skewness is also fairly high for some individual sectors, with an average of -0.57.

The fact that aggregate GDP is a linear combination of weakly asymmetric services and strongly asymmetric manufacturing determines our focus on manufacturing industries. We begin our empirical investigation with a nonlinear model for sector output in these industries.

3. ASYMMETRY IN THE MARKOV SWITCHING MODEL

Our paper tries to explain sector-level output growth asymmetries $\Delta Y_{n,t}$. We follow Clements and Krolzig (2003) by fitting an $m = 1, \ldots, M$-state regime-switching model at industry level $n = 1, \ldots, N$,

$$\Delta Y_{n,t} - \mu_{n,t}^{(m)} = \alpha_{n,0} + \sum_{r=1}^{R} \alpha_{n,r}\left(\Delta Y_{n,t} - \mu_{n,t-r}^{(m)}\right) + \varepsilon_{n,t}, \quad t = 1, \ldots, T, \quad \textbf{(1)}$$

where $\mu_{n,t}^{(m)}$ is the expectation of $\Delta Y_{n,t}$ conditional on being in state m and where $\varepsilon_{n,t} \sim N(0, \sigma_n^2)$. The Markov state changes are described by a transition probability matrix,

$$P_{n,t+1|t} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,M} \\ p_{2,1} & & & \\ \vdots & & & \\ p_{M,1} & p_{M,2} & \cdots & p_{M,M} \end{bmatrix}.$$

Compared to the direct measures of skewness that we used in Section 2 or nonparametric tests of skewness, the Markov switching model provides a convenient framework for jointly estimating the role of factors in output asymmetries. We estimate transition probability parameters, with and without factors in the conditional mean, that determine the degree of asymmetry. The model provides an interpretation of asymmetry as the expected duration of a cycle.

The economics literature has focused on three different types of asymmetries. What Sichel (1993) calls "deepness" emphasizes the relative magnitude of peaks and troughs during the cycle. If a similar asymmetry arises in the first difference of $\Delta Y_{n,t}$, the property is called "steepness." Finally, McQueen and Thorley (1993) define a "sharpness" asymmetry that arises if recessions are less persistent than expansions.

Clements and Krolzig (2003) clarify these concepts by defining asymmetries as restrictions on the regime switching process for output. In our model, the process is nondeep if

$$\sum_{m=1}^{M} \bar{\xi}_n^{(m)} \mu_n^{(m*)^3} = 0, \quad \textbf{(2)}$$

with $\mu_n^{(m*)} = \mu_n^{(m)} - \mu_n^{(\Delta Y)}$, where $\mu_n^{(\Delta Y)}$ is the unconditional mean of $\Delta Y_{n,t}$ and $\bar{\xi}_n^{(m)}$ is the unconditional probability of regime m for sector n. Intuitively, for a two-state Markov switching model the process is nondeep if the average depth of troughs $\mu_n^{(1)}$ and the average height of peaks $\mu_n^{(2)}$ are equidistant from the unconditional mean $\mu_n^{(\triangle Y)}$.

The process is nonsteep if

$$\sum_{i=1}^{M-1} \sum_{j=i+1}^{M} \left(\bar{\xi}_n^{(i)} p_{i,j} - \bar{\xi}_n^{(j)} p_{j,i}\right)\left[\mu_n^{(j)} - \mu_n^{(i)}\right]^3 = 0. \quad \mathbf{(3)}$$

Symmetry of the transition probability matrix is a sufficient but not necessary condition for nonsteepness. Clements and Krolzig (2003) prove that a two-state Markov switching model is always nonsteep even when the transition probability matrix is asymmetric.

Sharpness of the process implies the following restrictions on the transition probability of the model:

$$p_{m,1} = p_{m,M} \text{ and } p_{1,m} = p_{M,m} \qquad \forall m = 2, \ldots, M-1, \text{ and } p_{1,M} = p_{M,1}.$$

Later, we identify a two-state model as our leading case, and now rewrite our general expressions more compactly. In the case $M = 2$, $\bar{\xi}_n^{(1)} = p_{2,1}/(p_{1,2} + p_{2,1})$, as a result, 3 implies that steepness cannot exist. Clements and Krolzig (2003) also show that 2 implies that sharpness is a necessary condition for deepness. This enables us to focus solely on the more parsimonious sharpness test,[5]

$$R_n = p_{1,2} - p_{2,1}. \quad \mathbf{(4)}$$

To understand the intuition behind the statistic R_n, notice that $1/p_{1,2}$ is the expected duration of the expansion state 2, whereas $1/p_{2,1}$ is the average duration of the recession state 1. Negative estimates of R_n imply that the expected duration of recession is less than the expected duration of expansion. For a two-state model, this is equivalent to saying that the average depth of recessions $\mu_n^{(1)}$ is greater in absolute value than the average height of expansions $\mu_n^{(2)}$.

Confidence intervals for this statistic arise naturally in the estimation process we pursue. We now turn to describing our baseline model.

4. THE BASELINE MARKOV SWITCHING MODEL

In standard maximum likelihood estimation of Markov switching models, one has to keep track of the M^T possible values of the unobserved state sequence. Instead, we use a Bayesian approach to estimate the model. This simplifies the process of testing for multiple states and produces clean inference on the importance of specific parameters, test statistics, and the overall fit. Since it is not possible to describe the posterior distribution via analytical methods in this case, we estimate the model using Gibbs sampling. The idea of the method is to draw a large sample from a sequence of conditional posterior distributions that approximates the true posterior of the model. The advantage of the Bayesian method is that it allows a researcher to generate not only the model parameters but also the latent state variables. The details of estimation of the Markov switching models via Gibbs sampling can be found in Kim and Nelson (1998) or Chauvet et al. (2002).

4.1. Specification and Priors

Based on the stability of parameter estimates across our sectors and our inability to identify three states in acyclical nondurable industries, we chose to use a two-state model in the analysis. Based on the posterior odds ratio, we do not include lags of $\Delta Y_{n,t}$ in 1.

We follow the Kim and Nelson (1998) approach to identification and normalization. This approach can be demonstrated by rewriting (1) as

$$y_t = \mu_1 + \mu_2 S_t + e_t, \quad e_t \sim N(0, \sigma^2).$$

Note that μ_1 is the coefficient of a vector of ones, where μ_2 is a coefficient of a vector of zeroes and ones. For each draw we identify a recession state by imposing the restriction that it has a negative average growth rate. For every draw we impose $\mu_1 < 0$ and $\mu_2 > 0$, which implies that S_t takes on the value 1 in expansion and 0 in recession. Our prior mean is that output declines in recessions are 1.5 times larger than declines during expansions.[6]

Priors for $p_{1,1}$ and $p_{2,2}$ are independent beta distributions: $p_{1,1} \sim (u_{11}, u_{12})$, $p_{2,2} \sim (u_{22}, u_{21})$, where the u_{ij} are chosen so that $E(p_{1,1}) = 0.8$, $\text{Var}(p_{1,1}) = 0.1$, $E(p_{2,2}) = 0.9$, $\text{Var}(p_{2,2}) = 0.1$.

We used the Metropolis Hastings algorithm with 20,000 draws and a 5,000-observation burn. For each draw of the model parameters, the statistic R_n is computed and stored. These values are then used to estimate the posterior density and form empirical confidence intervals.

4.2. Results

The results in Table 2 show that the structural model provides evidence of asymmetry across a wide array of sectors. Manufacturing and durable and nondurable goods aggregates all have significant asymmetries.

In every sector but leather, food, and apparel, the probability of transiting out of recession, $p_{2,1}$, is higher than the probability of exiting an expansion, $p_{1,2}$. The most persistent contraction in the nondurables is food, with $p_{2,1} = 0.072$, and among the durables, industrial machinery, with $p_{2,1} = 0.216$. Expansions in durable goods output are most persistent in electronic machinery, $p_{1,2} = 0.059$, and printing and publishing for the nondurables, with $p_{1,2} = 0.031$.

The difference between the two transition probabilities, R_n, is our preferred measure of asymmetry. If sectoral output growth $\Delta Y_{n,t}$ is symmetric, the posterior distribution of R_n should be symmetric around a zero mean. As $\Delta Y_{n,t}$ becomes more asymmetric, the distribution of R_n shifts to the left reducing the area to the right of zero. We define p-mass as the probability of R_n taking values above zero,

TABLE 2. Markov switching tests of asymmetry model without factors

Sector	$p_{2,1}$	$p_{1,2}$	R_n	p-mass
Manufacturing	.2380	.0746	**−.1634**	0.0407
Durables	.2327	.0754	**−.1573**	0.0372
Lumber	.2947	.0594	**−.2353**	0.0267
Furniture	.2463	.0908	−.1555	0.2371
Stone clay glass	.2769	.0785	**−.1984**	0.0173
Primary metals	.2976	.0651	**−.2325**	0.0072
Fabricated metals	.3182	.0881	**−.2302**	0.0095
Industrial mach.	.2164	.0777	−.1387	0.1048
Electronic mach.	.3290	.0593	**−.2697**	0.0048
Transport. eq.	.2887	.0676	**−.2211**	0.0319
Instruments	.2379	.1400	−.0979	0.4976
Other manuf.	.4028	.0704	**−.3323**	0.0081
Nondurables	.2546	.0448	**−.2098**	0.0239
Food	.0716	.3071	.2355	0.1479
Tobacco	.2917	.0406	**−.2511**	0.0113
Textiles	.3194	.1530	−.1665	0.2113
Apparel	.1527	.1961	.0434	0.4657
Paper	.2310	.0381	**−.1929**	0.0437
Printing	.1776	.0309	−.1467	0.0564
Chemical	.2041	.0381	**−.1661**	0.0349
Petroleum	.3015	.0645	−.2370	0.1875
Rubber	.2519	.0559	**−.1960**	0.0257
Leather	.7629	.8423	.0794	0.5331
# significant at 5%			**14**	

Notes: $p_{2,1}$ is the probability of transiting out of recession. $p_{1,2}$ is the probability of transiting out of expansion. The statistic $R_n = p_{1,2} - p_{2,1}$ is from (4). The p-mass is the posterior distribution mass of R_n to the right of zero multiplied by 2 for normalization. A boldface sector indicates the p-mass for asymmetry is below 5%.

multiplied by two for normalization.[7] We adopt the following decision rule: $\Delta Y_{n,t}$ is asymmetric, that is, recessions are sharper and deeper than expansions, if the p-mass is below 5%.[8]

As in Rothman (2003), we find strong evidence of asymmetry in durable goods manufacturing and weaker evidence of asymmetry in nondurable sectors. At the 5% level, there are asymmetries in 7 of 10 durable sectors: lumber; stone, clay, and glass; primary metals; fabricated metals; electronics; transportation equipment; and other manufacturing. There are four nondurable asymmetric sectors: tobacco, paper, chemicals, and rubber.

Another conclusion from this analysis is that, judged by transition probabilities, the cyclical fluctuations vary across sectors substantially, which seems to contradict the finding of Bidarkota (1999).

5. FACTORS THAT MAY LEAD TO ASYMMETRY

This section draws upon the literature to explore asymmetric factors that might impact the manufacturing sector. First, we look at the production side, examining oil prices and producer price dispersion. Then, we examine factors on the demand side that have received less attention previously.

5.1. Oil Prices

There is a long literature in macroeconomics on the role of oil prices in the business cycle, dating back to Hamilton (1983). Hooker (2002) notes, however, that this relationship has weakened since 1981. Hamilton (2003) has recently argued that this changing relationship may be attributed to the misspecification of the functional form for output. In a flexible nonlinear model that includes the Markov switching model as a special case, he finds a strong relationship well beyond the mid-1980s.

Our interest in this question is not per se the impact of oil prices on economic growth, but rather their contribution to business cycle asymmetry. This question is also controversial. Raymond and Rich (1997) in a macro study and Davis and Haltiwanger (2001) in a micro study found an asymmetric effect of oil on output growth. Clements and Krolzig (2002) claim that the asymmetric effects of oil are not the complete source of skewness.

Following Hamilton (2003), we analyze[9] the real price increase of petroleum or_t by subtracting the producer price index pp_t inflation for the manufacturing sector from the Bureau of Labor Statistics producer price index series for domestic production of crude petroleum, o_t:

$$or_t = 100 \times [\Delta \ln(o_t/o_{t-1}) - \Delta \ln(pp_t/pp_{t-1})]. \tag{5}$$

This seemed to be the appropriate deflator for the sectors we considered above.

Lee et al. (1995) make the case for standardizing oil price shocks around some measure of time-varying volatility. An AR(4) for the conditional mean was chosen on the basis of the AIC. We then estimated the following GARCH(1,1) model using the Markov chain sampling approach of Nakatsuma (2000):

$$\begin{aligned} or_t &= 0.0993 + 0.1265 \times or_{t-1} - 0.1501 \times or_{t-2} \\ &\quad + 0.0137 \times or_{t-3} - 0.0850 \times or_{t-4} + \varepsilon_t, \end{aligned}$$

$$h_t = 29.2243 + 0.3362 \times h_{t-1} + 0.2799 \times \varepsilon_{t-1}^2. \tag{6}$$

We standardize the residual,

$$os_t = \varepsilon_t/\sqrt{h_t}, \tag{7}$$

and drop the negative shocks,

$$os_t^+ = \max(os_t, 0). \tag{8}$$

Both Hamilton (2003) and Clements and Krolzig (2002) agree that this measure captures much of the nonlinear (though not necessarily asymmetric) effect of oil prices on GDP.

Hamilton (2003) has also emphasized that military conflicts have caused nearly all the oil price shocks of the postwar period. He constructs a shock series for these periods of rapid price increase, 1956Q3, 1973Q3, 1978Q3, 1980Q3, and 1990Q2. We use this series as our second measure. Notice that the data are asymmetric by construction.

5.2. Relative Prices

Ball and Mankiw (1995) note that all supply shocks are changes in relative prices. The oil shocks in the previous section are changes in the price of petroleum relative to other goods. Ball and Mankiw build a theory on how these shocks can effect the general price level. They demonstrate that adjustments introduce a fundamental nonlinearity with only large shocks leading to sectoral price adjustment. Their model predicts that the variability and skewness of producer prices across sectors have a positive impact on the overall rate of inflation.

Ball and Mankiw introduce four measures[10] that they show both theoretically and empirically increase the rate of inflation. They all measure the cross-sectional variance and skewness of prices.

The most successful measure was the cross-sectional variance,

$$SV_t = \sum_{n=1}^{N} [\omega_n \Delta \ln(pp_{n,t}/pp_{n,t-1}) - \overline{pp}]^2/(N-1), \tag{9}$$

where ω_n is the sector weight in manufacturing output, $pp_{n,t}$ is the producer price index in sector n at time t, and $\overline{pp}$ is the cross-sectional average rate of inflation. We compute (9) for 460 four-digit producer prices in our eighteen sectors.

5.3. Leading Indicators

Schuh and Triest (1998) stress the need for additional research into the role of demand and expectations on job reallocation across sectors. They also note the difficulty in determining causality among aggregate shocks and sectoral shifts, a point that is stressed by Horvath (2000). To address both of these concerns, we turned to the empirical literature on leading business cycle indicators. From Stock and Watson (2002) and the Conference Board, we obtained seven demand-side covariates: (1) manufacturers' new orders: consumer goods and materials; (2) manufacturers' new orders: nondefense capital goods; (3) building permits, new private housing units; (4) real stock prices, S&P 500 index; (5) real M2 money supply; (6) term spread, ten-year Treasury bonds less the federal funds rate; (7) University of Michigan consumer sentiment index.

A deeper look at asymmetry now requires a return to our structural modeling framework.

6. MODEL ESTIMATES WITH FACTORS

Our empirical strategy is to reestimate the model with the factors from the previous section. For simplicity, we enter the factors one at a time, augmenting the baseline MSM with factors Z_{t-1} that impact sectors differently according to β_n,

$$\Delta Y_{n,t} - \mu_{n,t}^{(m)} = \beta_n Z_{t-1} + \alpha_{n,0} + \sum_{r=1}^{R} \alpha_{n,r}\left(\Delta Y_{n,t} - \mu_{n,t-r}^{(m)}\right) + \varepsilon_{n,t}, \quad t = 1, \ldots, T. \tag{10}$$

Each factor is lagged one quarter to avoid simultaneity issues. We then recompute our measure of asymmetry R_n. If a factor mitigates asymmetry so that a linear combination of $\Delta Y_{n,t}$ and a factor becomes symmetric, we conclude that the factor helps explain the output asymmetry in that sector.[11]

6.1. Supply Factors

We report estimates in Table 3 for the supply and demand factors. Boldface indicates sectors in which factors fail to mitigate asymmetry.

In the model without factors, we found that fourteen sectors and aggregates had significant output asymmetries. The best of our oil price variables, Hamilton's judgmental shocks, mitigates asymmetry in the three aggregates: aggregate manufacturing, durables, and nondurables. The impact is only marginally significant. All three would still reject symmetry at the 10% level. The only sectors that are strongly influenced by this shock are lumber and transportation equipment. The other oil price variables are less successful. Including os^+ does not push any sectors above the 5% threshold.

The cross-sectional variance of price dispersion is about as successful as the Hamilton series. SV strongly impacts nondurables asymmetry and marginally, manufacturing. It also marginally reduces asymmetry in other manufacturing and paper.

We conclude that if the supply side factors are a driving force in asymmetry they must be entering the model in some more complicated way than we have modeled here.

6.2. Demand Indicators

Here we begin our discussion of the demand side leading indicators. Real M2 has no impact on any of our sectors or aggregates. The effect of monetary policy on asymmetry appears to be operating through an interest rate channel. The spread between the ten-year bond and the federal funds rate is much more successful. It mitigates asymmetry from lumber, stone, fabricated metals, and other manufacturing on the durables side and paper, chemicals, and rubber on the nondurables side.

Orders for consumer goods and materials have an effect similar to the best supply side variable, Hamilton's shock. We still find asymmetry in ten sectors,

TABLE 3. Markov switching model with factors

Sector	No factors	os^+	H-shock	SV	Real M2	Ord. cap.	Ord. con.	Stocks	Permits	Spread	Expect
Manufacturing	**0.0407**	**0.0385**	0.1092	0.0555	**0.0413**	**0.0441**	**0.0415**	0.0516	0.7009	0.1643	0.8463
Durables	**0.0372**	**0.0355**	0.0625	**0.0289**	**0.0332**	**0.0367**	**0.0293**	**0.0315**	0.7431	**0.0144**	0.2928
Lumber	**0.0267**	**0.0305**	0.3936	**0.0395**	**0.0473**	0.1809	**0.0248**	0.0745	0.2069	0.9971	0.2441
Furniture	0.2371	0.1939	0.1259	0.1963	0.1536	0.2428	0.4596	0.2797	0.3751	0.7600	0.3973
Stone clay glass	**0.0173**	**0.0207**	**0.0331**	**0.0220**	**0.0211**	**0.0105**	0.0517	0.0593	**0.0273**	0.4792	0.2113
Primary metals	**0.0072**	**0.0055**	**0.0053**	**0.0039**	**0.0044**	**0.0071**	**0.0076**	**0.0045**	**0.0228**	**0.0067**	**0.0051**
Fabricated metals	**0.0095**	**0.0069**	**0.0081**	**0.0111**	**0.0107**	**0.0140**	0.1737	**0.0285**	0.1020	0.3766	0.3285
Industrial mach.	0.1048	**0.0408**	0.0887	0.0909	0.0720	0.0603	**0.0465**	0.0684	0.4164	**0.0300**	0.4668
Electronic mach.	**0.0048**	**0.0053**	**0.0063**	**0.0039**	**0.0044**	**0.0097**	**0.0055**	**0.0063**	**0.0071**	**0.0044**	**0.0191**
Transport. eq.	**0.0319**	**0.0392**	0.3501	**0.0477**	**0.0380**	**0.0295**	**0.0193**	0.0636	0.0540	0.6156	0.0871
Instruments	0.4976	0.3004	0.3199	0.3456	0.3117	0.3132	0.3027	0.4147	0.4171	0.6757	0.5851
Other manuf.	**0.0081**	**0.0160**	**0.0236**	0.0588	**0.0185**	**0.0480**	**0.0135**	**0.0200**	**0.0145**	0.0629	0.0713
Nondurables	**0.0239**	**0.0276**	0.0588	0.3681	0.0556	0.0597	0.0609	0.1448	**0.0417**	0.2769	0.4161
Food	0.1479	**0.0224**	0.2506	0.1543	0.2412	0.2425	0.1513	0.1266	0.1405	0.0513	0.1187
Tobacco	**0.0113**	**0.0120**	**0.0156**	**0.0148**	**0.0159**	**0.0152**	**0.0139**	**0.0155**	**0.0120**	**0.0141**	**0.0139**
Textiles	0.2113	0.5567	0.2593	0.4244	0.2491	0.4800	0.9629	0.1588	0.6335	0.9075	0.9733
Apparel	0.4657	0.3151	0.3953	0.3115	0.9575	0.1577	0.2383	0.1493	0.1531	0.0365	0.3203
Paper	**0.0437**	**0.0479**	**0.0424**	0.0871	**0.0444**	0.0561	0.1205	**0.0361**	0.0943	0.1107	0.0852
Printing	0.0564	0.0605	0.0508	0.0871	0.0565	0.0717	0.0677	0.0576	0.0751	0.0931	0.0599
Chemical	**0.0349**	**0.0348**	**0.0305**	**0.0373**	**0.0373**	**0.0395**	**0.0401**	**0.0420**	**0.0387**	0.0897	0.0693
Petroleum	0.1875	0.0964	**0.0189**	**0.0485**	**0.0359**	0.2849	0.4445	0.3399	**0.0408**	**0.0444**	0.2076
Rubber	**0.0257**	**0.0219**	**0.0273**	**0.0339**	**0.0211**	**0.0367**	0.0767	**0.0387**	0.0791	0.4771	0.2871
Leather	0.5331	0.4175	0.5056	0.3761	0.5196	0.3411	0.4219	0.6835	0.1601	0.3013	0.4961
# significant at 5%	**14**	**16**	**10**	**11**	**14**	**11**	**10**	**9**	**8**	**6**	**3**

Notes: The entries are p-masses for the asymmetry in R_n from (4) after including the factor. Boldface indicates p-mass at the 5% level or lower. SV, the cross-section variance of price dispersion, is given by (9). os^+ is the positive shocks to os as in (8). H-shock is a judgmental series of oil price shocks corresponding to periods of severe shortages introduced in Hamilton (2003). Real M2 is the real M2 money supply. Ord. cap. are new orders for nondefense capital goods. Ord. con are orders for consumer goods and materials. Stocks is the return on the S&P 500 index. Permits is new building permits for single family homes. Spread is the spread between the 10-year bond and the federal funds rate. Expect is consumer expectations from the U. of Michigan. All factors are lagged one time period.

though. Orders for nondefense capital goods are essentially the same, except for a smaller impact on the rubber sector.

Stocks prices are slightly more successful than orders, mitigating asymmetry in five sectors. The building permits makes asymmetry insignificant in six. Permits have an especially strong impact on aggregate manufacturing and durables.

Our best evidence for a demand side asymmetric driving force in the business cycle comes from consumer expectations. Consumer expectations remove asymmetry from all but *three* sectors: primary metals, electronic machinery, and tobacco. Although some of the asymmetry reductions are marginal, other manufacturing, transportation equipment, paper and chemicals are still asymmetric at the 10% level, the other reductions are substantial. The average increase in the p-mass in the other seven sectors is 35%. Aggregate manufacturing, durables, and nondurables are all symmetric even at the 25% level.

To test the statistical significance of this overall reduction, we compare the sum of the p-mass of our 23 sectors and aggregates before and after we include the consumer expectation factor. The average difference between the sums in 15,000 MCMC draws[12] is -3.144 with a standard deviation of 1.12 and a 95% highest posterior density interval of $(-5.38, -1.06)$. The overall asymmetry reduction is statistically significant.

We conclude with a good understanding of the aggregate driving force. We have identified consumer expectations as a factor that can explain more than $3/4$ of the asymmetry we found in the sectors.

In the working paper version of this manuscript,[13] we analyzed asymmetry at the firm level. Our findings support the view that shocks may originate on the demand side, but the production side plays an important role in how the shocks are smoothed. Asymmetric sectors have a higher bankruptcy risk, a lower level of finished goods, and a higher level of raw materials inventory and are more capital- and energy-intensive, all of which make it harder to mitigate asymmetric demand shocks.

7. CONCLUSION

The manufacturing sector is crucial to understanding business cycle asymmetry. Durable goods output recessions are deep, and this is reflected in the asymmetry we detect in seven of ten durable goods sectors. Nondurable goods sectors are less asymmetric, but we still detect asymmetry in four of ten sectors and in aggregate durables and nondurables.

We find that these deep recessions are driven by demand side factors including the term spread and consumer expectations. Once we control for the factors, the amplitude of recessions in most sectors becomes comparable to the amplitude of expansions.

Our empirical results, we feel, point toward both the critical role of manufacturing in business cycle fluctuations and the types of shocks that induce asymmetries in output.

NOTES

1. SIC is the now obsolete Standard Industrial Classification system. Gradually, most agencies have shifted to the NAICS, the North American Industrial Classification System of the Census Bureau. Historical data for many variables go back only to 1972, and we opted to use the SIC measures.

2. The data can be downloaded from the BEA at http://www.bea.gov/national/nipaweb/nipa_underlying/SelectTable.asp.

3. We follow Blinder (1986) by including the entire change in inventories in output, rather than using the NIPA definition, which only includes finished goods. The two output measures have a correlation of 0.986 for durables and 0.989 for nondurables and the choice had little qualitative impact on the results.

4. Results with NAICS industrial production indices are similar and available upon request.

5. Although Clements and Krolzig are the first to derive the link between asymmetry and the transition probabilities, the Bayesian test is ours.

6. An analysis of presample data from 1958 to 1966 had a mean scaling factor of 1.4 for the 12 two-digit SIC industries that experienced at least two quarters of declines in recessions in the period. We investigated the robustness of the scaling factor over the range from 0.5 to 2.0 and found that our results about the sectoral characteristics are robust to the choice of prior.

7. It is equal to 1 when the distribution of R_n is symmetric around zero and the probability of R_n taking values above zero is 50%.

8. This implies that the mass of R_n to the right of zero is lower than 2.5%.

9. In the working paper version of this manuscript, we considered five alternative measures of oil prices. The first was the series of real price changes, or_t. Many authors have reasoned that petroleum prices matter only when they are rising. We used the positive changes directly and also compared the increases to 4- and 12-period maxima. We also analyzed the standardized residual (7). These measures captured the asymmetry in no more than two sectors, so we omit them from Table 3.

10. The other measures we tested included the skewness, $\text{Skew}_t = \sum_{n=1}^{N}[\omega_n \Delta \ln(pp_{n,t}/pp_{n,t-1}) - \overline{pp}]^3/[(N-1)\text{Var}_t^{1/2}]$, and the variability, $\text{Var}_t = \sum_{n=1}^{N}[\omega_n \Delta \ln(pp_{n,t}/pp_{n,t-1}) - \overline{pp}]^2/(N-1)$. We also measured the tail area directly, $\text{Asy}X_t = \sum_{n=1}^{N}[\overline{pp}_X - \omega_n \Delta \ln(pp_{n,t}/pp_{n,t-1})]^+ + [\omega_n \Delta \ln(pp_{n,t}/pp_{n,t-1}) - \overline{pp}_{1-X}]^+$, where $\overline{pp}_X$ is the Xth percent fractile of the distribution. Finally, we tested a measure that weights the absolute price changes, $Q_t = \sum_{n=1}^{N} \omega_n \left|\Delta \ln(pp_{n,t}/pp_{n,t-1})\right| \times \Delta \ln(pp_{n,t}/pp_{n,t-1})$. These measures captured asymmetry in no more than two sectors and are not listed in Table 3.

11. Following a referee's suggestion, we investigated the possibility that industry input-output relationships are the driving force behind asymmetry. We included the lagged output of our asymmetric sectors as a factor in (10), but the most influential sector, electrical machinery, only captured the asymmetry in six sectors. Results are available upon request.

12. The p-mass is calculated for each 100 draws, so averages and intervals are based on a sample of 1,500 observations.

13. Available at http://ssrn.com/abstract=1026486.

REFERENCES

Ball, Larry and N. Gregory Mankiw (1995) Relative price changes as aggregate supply shocks. *Quarterly Journal of Economics* 110, 161–193.

Bidarkota, Prasad (1999) Sectoral investigation of asymmetries in the conditional mean dynamics of the real U.S. GDP. *Studies in Nonlinear Dynamics & Econometrics* 3(4), Article 2.

Blinder, Alan (1986) Can the production smoothing model of inventories be saved? *Quarterly Journal of Economics* 101, 431–454.

Chauvet, Marcelle, Chinhui Juhn, and Simon Potter (2002) Markov switching in disaggregate unemployment rates. *Empirical Economics* 27, 205–232.

Clements, Michael and Hans-Martin Krolzig (2002) Can oil shocks explain asymmetries in the US business cycle? *Empirical Economics* 27, 185–204.

Clements, Michael P. and Hans-Martin Krolzig (2003) Business cycle asymmetries: Characterization and testing based on Markov-switching autoregressions. *Journal of Business and Economic Statistics* 21, 196–211.

Davis, Steven J. and John Haltiwanger (2001) Sectoral job creation and destruction responses to oil price changes. *Journal of Monetary Economics* 48, 468–512.

Fok, Dennis, Philip Hans Franses, and Dick van Dijk (2005) A multi-level panel STAR model for US sectoral production. *Journal of Applied Econometrics* 20, 811–827.

Hamilton, James (1983) Oil and the macroeconomy since World War II. *Journal of Political Economy* 91, 228–248.

Hamilton, James (2003) What is an oil shock? *Journal of Econometrics* 113, 363–398.

Hooker, Mark A. (2002) Are oil shocks inflationary? Asymmetric and nonlinear specifications versus changes in regime. *Journal of Money, Credit and Banking* 34, 540–561.

Horvath, M. (2000) Sectoral shocks and aggregate fluctuations. *Journal of Monetary Economics* 45, 69–106.

Kim, Chang Jin, and Charles R. Nelson (1998) *State Space Models with Regime Switching: Classical and Gibbs-Sampling Approaches with Applications.* Cambridge, MA: MIT Press.

Krolzig, Hans-Martin and Marianne Sensier (2000) A disaggregated Markov switching model of the business cycle in U.K. manufacturing. *Manchester School* 68, 442–460.

Lee, Kiseok, Shawn Ni, and Ronald Ratti (1995) Oil shocks and the macroeconomy: The role of price variability. *Energy Journal* 16, 39–56.

McQueen, Grant and Steven Thorley (1993) Asymmetric business cycle turning points. *Journal of Monetary Economics* 31, 341–362.

Nakatsuma, Teruo (2000) Bayesian Analysis of ARMA—GARCH models: A Markov chain sampling approach. *Journal of Econometrics* 95, 57–69.

Raymond, Jennie E. and Robert Rich (1997) Oil and the macroeconomy: A Markov state-switching approach. *Journal of Money, Credit and Banking* 29, 193–213. Erratum 29, 555.

Razzak, Weshah (2001) Business cycle asymmetries: International evidence. *Review of Economic Dynamics* 4, 230–243.

Rothman, Philip (2003) Reconsideration of the Markov Chain Evidence on Unemployment Rate Asymmetry. Working paper, Department of Economics, East Carolina University.

Schuh, Scott and R. K. Triest (1998) Job reallocation and the business cycle: New facts and old debate. In Jeffrey Fuhrer and Scott Schuh (eds.), *What Causes Business Cycles.* Boston Federal Reserve Bank Conference Volume 42, 271–337.

Sichel, Daniel E. (1993) Business cycle asymmetry: A deeper look. *Economic Inquiry* 31, 224–236.

Stock, James and Mark Watson (2002) Has the business cycle changed and why? In Mark Gertler and Ken Rogoff (eds.), *NBER Macroeconomics Annual*, pp. 159–218. Cambridge, MA: MIT Press.