The Microeconomics of Macroeconomic Asymmetries: Sectoral Driving Forces and Firm Level Characteristics

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Abstract

There is now considerable evidence that business cycle variation in output and employment in the U.S. differs in expansions and contractions. We present nonparametric evidence that asymmetries are strongest in durable goods manufacturing. In a Markov switching framework, we find two leading indicators, consumer expectations and the term spread, act as important driving forces behind asymmetry. Cross sectional analysis, using firm level data, shows that plant and equipment expenditures, raw materials inventory holdings, and bankruptcy score increase the likelihood ratio index for asymmetry by more than 65%.

`Keywords`: asymmetry; industry; triples test; Markov switching; oil prices; inventories; leading indicators.

`JEL Classification`: E23, E24, E32.

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There is now considerable evidence that business cycle expansion and contraction phases are distinct. Production asymmetries in the U.S. economy have been detected by, among others Hamilton (1989) and Clements and Krolzig (2003). Another group of papers has examined the unemployment rate, as in Neftci (1984), Rothman (1991, 2003) or Chauvet, Juhn, and Potter (2002). Altissimo and Violante (2001) model both output and unemployment jointly. Research by Ramsey and Rothman (1996), Verbrugge (1998), Razzak (2001), Mayes and Viren (2002), and Kim, Morley and Piger (2002) provide support for asymmetry internationally.

The source of the asymmetry is not very well understood though. Several papers provide some tantalizing clues. Disaggregated studies such as Rothman (2003) find significant evidence of asymmetric unemployment rates in manufacturing, particularly durable goods. There is less evidence for asymmetry in either nondurable goods manufacturing or agriculture. Fok, Franses, and van Dijk (2003) find differences in the timing of recession across sectors. Krolzig and Sensier (2000) detect common business cycle features in U.K. manufacturing sectors. Bidarkota (1999) is skeptical of important sectoral differences though.

The literature has given considerable attention to inventories and oil prices, although generally at the aggregate level. Sichel (1994) provides support for inventories as the source of output asymmetry. He finds that GDP is asymmetric, but final sales, which subtract out inventories, are not. Sensier (2003) finds that work-in-progress inventories in U.K. manufacturing exhibit the same kind of asymmetry that the sector as a whole experiences.

Raymond and Rich (1997), Davis and Haltiwanger (2001), Hooker (2002), and Hamilton (2003) believe that petroleum is the key factor. They find that oil price shocks effect employment growth asymmetrically, with price increases leading to layoffs but not new hiring when prices fall. Clements and Krolzig (2002) find contrary evidence when they look at a more aggregate level. They find more asymmetry in the expansion phase of the business cycle, not the downturns.

Schuh and Triest (1998) observe that most research has focused on supply side sources of asymmetry. The role for a demand side channel in layoffs is considered in Hall (1999). Real interest rate shocks lead firms to shut down and eliminate jobs. Davis and Haltiwanger (2001) find job reallocation is more volatile in less mature plants, which they note may be a proxy for credit conditions. Lo and Piger (2004) note that monetary policy is much more effective in a recession but leave open the question of why. Peersman and Smets' (2002) explanation for the Euro area is the industry financial structure.

We propose a factor augmented, sector level Markov switching model in which we can evaluate a variety of empirical explanations. Our results support an important role for demand factors as a driving force in asymmetry. We find that two demand side leading indicators, consumer expectations and the term spread, are a factor in nearly 2/3 of manufacturing industries. Production side factors, like inventories and oil prices, drive the sectoral asymmetry in only a handful of industries.

After modeling the economy wide asymmetry, we next turn to firm level data for over 3,200 companies. We consider the characteristics of the sectors that are not able to smooth out these asymmetric business cycle factors. At the firm level, we do find a role for production characteristics. Industries are more likely to be asymmetric if they have a high raw materials inventory to sales ratio, are energy intensive, and make larger plant and equipment expenditures. Credit conditions also matter at the firm level. Asymmetric industries have a higher bankruptcy risk as measured by Altman's Z-score.

We begin our formal analysis with a look at the data from a nonparametric perspective in Section 1. The discussion of factors that might explain asymmetry in manufacturing is in Section 2. The factor augmented Markov switching model is developed in Section 3, and estimation results are in Section 4. Section 5 contains our discussion of firm level data. Section 6 concludes with some of the implications for business cycle modeling.

1. Nonstructural Data Analysis

Sichel (1993) noted that expansions often consist of smaller deviations of levels from trend than contractions. He called this property *deepness*. If the same property applies to growth rates, the series is said to possess *steepness*. To better understand the sectors and kinds of asymmetries, this section tests for steepness and deepness in all of the aggregate, sectoral and factor series.

Our nonparametric analysis of the data relies on the triples test of Randles, Flinger, Policello and Wolfe (1980) which was adapted by Verbrugge (1997). The triples test has better power than Sichel's test based on the coefficient of skewness and cannot be dominated by outliers. The construction of the triples test is described in Appendix A.

The sample period throughout is quarterly from January 1967 to December 1997. This coincides with our sample of sectoral data. There are 5 NBER recessions in the time period which ends well into the last expansion cycle. We detrend the data by taking log differences, except for inventories where we take simple differences. Our analysis begins with output at the aggregate level.

1.1 Aggregates

Table 1 reports no evidence for asymmetry in aggregate GDP. The p-value on the triples test is 0.69 for deepness and 0.53 for steepness. These results are largely consistent with the recent literature, including Razzak (2001), that finds weak evidence for asymmetry in output series in the U.S.

[Insert Table 1 Here]

The lack of either deepness or steepness in aggregate GDP requires going to a more disaggregated level. We think that many of the contradictory explanations in the literature for asymmetry may be resolved at the sectoral level.

1.2 Sectors

Rothman (2003) found unemployment asymmetries in manufacturing industries. We confirmed his results for production using quarterly durable and nondurable goods output. These two findings led us to do our disaggregated analysis on the manufacturing sector.

We collected sales and inventory data for January 1967 to December 1997 on durables and nondurables manufacturing sectors[1]. We convert the data to a quarterly frequency. 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); (11) Other manufacturing durables (SIC 39).

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).

[Insert Table 2 Here]

Table 2 reports results for these sectors for the deepness asymmetry in final sales. There is evidence for steepness in durable goods manufacturing at the 7% level, but there is no evidence for asymmetry in nondurables.

There is a deepness asymmetry in 5 of 10 durable sub-sectors at the 10% level or better: stone

[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. Unfortunately, this leaves us with time series for many sectors too short for analysis.

clay and glass, primary metals, fabricated metals, industrial machinery, and electronic machinery. Transportation equipment has a significant steepness asymmetry. Only one nondurable sector is asymmetric, textiles, with a strong rejection on the deepness test.

This nonstructural analysis primarily identifies asymmetry in durable goods manufacturing industries. We next look for the driving forces behind the asymmetry.

2. Explanatory Factors

We look for two general categories of the factors behind asymmetry. Roughly speaking, some are inherent to the production process, like inventories and oil prices. We also look for factors on the demand side which have received less attention previously.

2.1 Inventories

Inventories are known to be an important component of the business cycle. While they represent a relatively small share of total output, inventories often explain more than half the sectoral variance. McConnell and Perez-Quiros (2000) attribute much of the recent decline in GDP volatility to improved inventory management techniques.

Sichel (1994) has claimed that inventories are also an important factor in output asymmetry. Begin with the production identity[2]

$$Y_{n,t} = S_{n,t} + \Delta I_{n,t}, \tag{1}$$

where Y_n is the output of sector n, S_n is sales, and I_n is inventories. Sichel observes asymmetry in aggregate GDP during his sample, but not sales. He then attributes the asymmetry to the inventory process. Our results for aggregate output in Table 1 differ from Sichel's. Breaking the GDP series into final sales and inventories reveals no asymmetry in either component.

We also examined Sichel's conjecture at the sectoral level by testing for asymmetries in all three components of inventories: finished goods, work-in-process and raw materials. We begin with finished goods inventory in Table 2.

None of the aggregates, overall manufacturing, durables or nondurables have any evidence of asymmetry. One durable subsector, electronic machinery, has deepness asymmetry, and electronic

[2] 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 had little qualitative impact on the results.

machinery and industrial machinery have steepness. None of the nondurable subsectors has either deepness or steepness. It may turn out that finished goods do effect asymmetry through some nonlinear mechanism, but at this stage, we can conclude that it is not entering linearly through the production process.

We now turn to inventories at more intermediate stages of processing, work-in-process and materials and supplies. Sensier (2003) has found a mild steepness asymmetry in U.K. aggregate work-in-process inventory, but not in any other inventory stages or in aggregate output. We do not find strong evidence in the U.S. when we look at the sectoral level in Table 2. We find only one significant deepness asymmetry, in the instruments sector. There are no other steepness or deepness asymmetries in any sectors or any of the aggregates.

There is somewhat more statistical evidence of asymmetry in the materials series in Table 2. There are two durable goods series with a deepness asymmetry, stone clay and glass and instruments. One nondurable sector, paper, shows deepness. The food sector shows steepness. While four sectors have some evidence of asymmetry, we still do not see it in any of the aggregates. We remain cautious about any final conclusions for all three levels of inventories until we see their impact in the structural model.

We turn now to another explanatory variable that has received much attention in the literature, oil shocks.

2.2 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 on the expansion phase of the cycle, and are not the complete source of skewness.

We consider seven different measures of oil prices. Following Hamilton (2003), we first analyze the Bureau of Labor Statistics producer price index series for domestic production of crude petroleum, o_t. The series is not seasonally adjusted, appears monthly, and has a base year of 1982. We analyze the percentage change. Many authors have reasoned that petroleum prices matter only when they are rising, so we consider two cases: the first, the percentage increase over the high price for the last 4 quarters; the second looks at a 12 quarter high. We consider the real price increase of petroleum by subtracting off the producer price index pp_t inflation for the manufacturing sector

$$or_t = 100 \times (\Delta \ln(o_t/o_{t-1}) - \Delta \ln(pp_t/pp_{t-1})). \tag{2}$$

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

Lee, Ni and Ratti (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),

$$or_t = 0.0993 + 0.1265 \times or_{t-1} - 0.1501 \times or_{t-2} + 0.0137 \times or_{t-3} - 0.0850 \times or_{t-4} + \varepsilon_t, \tag{3}$$

$$h_t = 29.2243 + 0.3362 \times h_{t-1} + 0.2799 \times \varepsilon_{t-1}^2. \tag{4}$$

The shock series, our fifth price measure, is the standardized residual,

$$os_t = \varepsilon_t/\sqrt{h_t}. \tag{5}$$

Following Lee, Ni and Ratti (1995), we also include a measure that drops the negative shocks

$$os_t^+ = \max(os_t, 0). \tag{6}$$

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 post-war period. He constructs a shock series for these periods of rapid price increases, 1956Q3, 1973Q3, 1978Q3, 1980Q3 and 1990Q2. We use this series as our seventh measure.

We begin our analysis of this data by looking at the asymmetry in these series before using it to explain sectoral production aggregates.

[Insert Table 3 Here]

Notice that except for o_t, or_t, and os_t, the data are asymmetric by assumption. The triples test in Table 3 provides us little additional information because these are the only three that do not present a deepness asymmetry. None of the variables has the steepness property.

2.3 Demand 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. 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, 10-year Treasury bonds less the federal funds rate; (7) University of Michigan consumer sentiment index.

[Insert Table 4 Here]

We perform the triples test on these series in Table 4. There are five series which show asymmetry at the 10% level. Orders for nondefense capital goods, building permits, the term spread and consumer expectations have a deepness asymmetry. Three series have steepness, nondefense orders, building permits, and stock prices. The M2 money supply and orders for consumer goods show neither asymmetry.

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

3. A Factor Augmented Markov Switching Model

The Markov switching (MS) framework introduced by Hamilton (1989) provides a modeling structure for understanding stylized facts about business cycles. Our paper extends Clements and Krolzig (2003) by fitting an $m = 1, \ldots, M$ state regime switching model for output at the industry level $n = 1, \ldots N$,

$$X_{n,t} - \mu_{n,t}^{(m)} = \textstyle\sum_{r=1}^{R} \alpha_{n,r}(X_{n,t-r} - \mu_{n,t-r}^{(m)}) + \varepsilon_{n,t},\ t = 1, ..., T, \tag{7}$$

and including aggregate or industry level driving forces

$$X_{n,t} = Y_{n,t} - \beta_n Z_{n,t-1}, \tag{8}$$

with

$$\varepsilon_{n,t} \sim N(0, (\sigma_{n,t}^{(m)})^2). \tag{9}$$

$Z_{n,t}$ is a variable representing sector characteristics like inventories or aggregate shocks like oil prices, β_n are parameters we estimate for each sector, $\mu_{n,t}^{(m)}$ is the expectation of $X_{n,t}$ conditional on being in state m. We will try to identify which factors remove asymmetry from industry output.

This model allows a heteroskedastic error term and was first analyzed by McConnell and Perez-Quiros (2000). It is an extension of the standard Hamilton model, which is governed by a single Markov switching state. The Markov state changes are described by a transition probability matrix,

$$P_{n,t+1|t} = \begin{bmatrix} p_{1,1} & p_{2,1} & \cdots & p_{M,1} \\ p_{1,2} & & & \\ \vdots & & & \\ p_{1,M} & p_{2,M} & \cdots & p_{M,M} \end{bmatrix}. \tag{10}$$

In standard maximum likelihood estimation of this type of models one has to keep track of the M^T possible values of the Markov sequence. We instead 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 and 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 variables. The details of estimation of the Markov switching models via Gibbs sampling can be found in Kim and Nelson (1998) or Chauvet, Juhn and Potter (2002).

We follow Clements and Krolzig (2003) by expressing asymmetries as restrictions on the regime switching process for output. In our model, the process is nondeep if

$$R_{1,n} \equiv \sum_{m=1}^{M} \bar{\xi}_n^{(m)} {\mu_n^{(m*)}}^3 = 0, \tag{11}$$

with $\mu_n^{(m*)} = \mu_n^{(m)} - \mu_n^{(x)}$, where $\mu_n^{(x)}$ is the unconditional mean of $X_{n,t}$ and $\bar{\xi}_n^{(m)}$ is the unconditional probability of regime m for sector n. We test for nondeepness by determining whether the 90% posterior density interval of the statistic $R_{1,n}$ includes zero.

The process is nonsteep if

$$R_{2,n} \equiv \sum_{i=1}^{M-1} \sum_{j=i+1}^{M} (\bar{\xi}_n^{(i)} p_{i,j} - \bar{\xi}_n^{(j)} p_{j,i})[\mu_n^{(j)} - \mu_n^{(i)}]^3 = 0. \tag{12}$$

We test for nonsteepness using the 90% posterior density interval of $R_{2,n}$.

This model can incorporate a third kind of asymmetry known as *sharpness* which relates to the persistence of business cycle states. McQueen and Thorley (1993) detected sharpness when they estimated recessions as less persistent than expansions.

To test the sharpness proposition, we need to consider the case where $M \geq 2$. Sharpness of the process implies the following restrictions on the transition probability of the model

$$p_{m,1} = p_{m,M} \text{ and } p_{1,m} = p_{M,m} \; \forall m = 2, ..., M-1, \text{ and } p_{1,M} = p_{M,1}. \tag{13}$$

These restrictions can also be tested using highest posterior density intervals (HPDI).

To derive the posterior densities of test statistics $R_{1,n}$ and $R_{2,n}$, we use the simulated Markov Chain Monte Carlo (MCMC) parameters. To obtain estimates of unconditional probabilities of each regime, ξ_n, we extract an eigenvector that corresponds to the first eigenvalue of the transition probability matrix P.

4. Results

Currently, the popular choice at the aggregate level for model (7) is either the 2- or 3-state Markov switching (MS) model with homoskedastic or heteroskedestic error term. Based on the stability of parameter estimates across our 25 sectors, the ability of the model to estimate the NBER dated recessions, and our inability to identify three states in acyclical nondurable industries, we chose to use the homoskedastic 2-state model in the analysis.

In the case $M = 2$, (12) implies that $\bar{\xi}_n^{(1)} = p_{2,1}/(p_{1,2} + p_{2,1})$ and $\bar{\xi}_n^{(2)} = p_{1,2}/(p_{1,2} + p_{2,1})$, as a result, $R_{2,n} = 0$ independent of $p_{1,2}$ or $p_{2,1}$. It follows that in the 2-state model, steepness cannot exist. Clements and Krolzig (2003) also show that sharpness is a necessary condition for deepness. While we calculate both deepness and sharpness throughout the paper as a robustness check, we will report only the results for the more parsimonious sharpness test,

$$R_{3,n} = p_{2,1} - p_{1,2}. \tag{14}$$

Our prior mean was that output declines in recessions are 1.5 times larger than declines during an expansion.[3] Based on the posterior odds ratio, the lag length was set at $R = 0$.

We used the Metropolis Hastings algorithm with $20,000$ replications and a $5,000$ observation burn. For each draw of the model parameters, the statistics $R_{1,n}$ and $R_{3,n}$ are computed and

[3] An analysis of pre-sample 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 a range from 0.5 to 2.0 and found our results about the sectoral characteristics robust to the choice of prior.

stored. These values are then used to estimate the posterior density and the 90% HPDI. The test will reject symmetry if the interval does not include zero.

4.1 Model without factors

We begin our analysis with a discussion of the model (7) without factors where $X_{n,t} = Y_{n,t}$. The results in Table 5 show that the structural model provides stronger evidence of asymmetry beyond the triples test. Manufacturing, durable and nondurable good aggregates all have significant asymmetries.

[Insert Table 5 Here]

There are asymmetries in 6 of 10 durable sectors: lumber, stone clay and glass, primary metals, fabricated metals, electronics, and transportation equipment. These are consistent with the triples test except for furniture, instruments, and other manufacturing which are no longer found to be asymmetric.

There are four nondurable sectors with significant asymmetries: tobacco, textiles, chemicals and rubber. These all differ from what we found in the triples test except for textiles.

We now turn to see if any of our factors can explain the differences across sectors.

4.2 Factor models

We only include as factors variables that we found to be asymmetric in the triples test. Since the factors enter linearly, there must be asymmetry in the factor series to explain asymmetry in output. Each factor is lagged one quarter.

We examine raw materials inventories, a representative oil price measure, and the asymmetric leading indicators as factors. If the variables are helping to explain the sectoral differences, we would expect the Markov switching test to no longer reject that the series is symmetric. Results for the sharpness test are in Table 6. An X marks sectors that still have asymmetry after including the factor.

4.2.1 Inventories

We limit our discussion to raw materials inventories because they are the most asymmetric of all three inventory types as measured by the triples test.

[Insert Table 6 Here]

Raw materials inventories mitigate asymmetry in only one sector: aggregate manufacturing. Asymmetry still remains in aggregate durables and nondurables. There is still remaining asymmetry in six durable sectors, and three nondurable sectors. On the whole, we think this factor leaves room for alternative explanations.

4.2.2 Oil prices

We report estimates in Table 6 for the most successful oil price variable, the standardized positive real oil price shocks (6) studied by Lee, Ni and Ratti (1995). It had the strongest results on the triples test.

Including this variable as a factor adds almost as much asymmetry as it explains. It removes asymmetry from lumber products and textiles but adds asymmetry to food. We conclude that if oil is a driving force in asymmetry it must be entering the model in some more complicated way than we have modeled here.

4.2.3 Demand indicators

Here we begin our discussion of the five asymmetric demand side leading indicators. Orders for nondefense capital goods is as unsuccessful as inventories or oil prices. It adds asymmetry to one durable sector, other manufacturing, and one nondurable sector, paper and printing.

The building permits variable is more successful than the orders variable. It eliminates asymmetry in transportation equipment and textiles. It also removes asymmetry in two aggregates, durables and manufacturing. Stock prices are similar to building permits. They remove asymmetry from textiles, and all three aggregates, nondurables, durables and manufacturing.

Our best evidence for a demand side asymmetric driving force in the business cycle comes from consumer expectations and the term spread. Consumer expectations remove asymmetry from three durable sectors, lumber, stone, and transportation, and three nondurable sectors, textiles, chemicals, and rubber. They also remove asymmetry from all the aggregates. This indicator, however, does add asymmetry to one sector, paper. The term spread between the 10-year Treasury bond and federal funds rate removes asymmetry from lumber, stone, and fabricated metals on the durables side, and textiles, chemicals and rubber on the nondurables side. Aggregate nondurables and manufacturing also become symmetric, but durables do not. It also introduces asymmetry into industrial machinery.

We conclude with a good understanding of the aggregate driving force. We have identified two factors each of which can explain more than 2/3 of the asymmetry we found in the sectors. As we turn to a firm level analysis, we intend to look further at characteristics which influence the ability of individual firms to smooth these asymmetric demand factors.

5. Cross Sectional Analysis

Our factor analysis has helped to identify aggregate driving forces for business cycle asymmetry. In this section, we turn to examine industry characteristics that may explain why some sectors seem to be able to smooth these asymmetric processes.

We lack long quarterly time series on most of these data. Our empirical methodology is then restricted to a Bayesian probit analysis[4] for the presence of asymmetry. We evaluate models on the basis of marginal likelihood of the model or the Bayes' factor. As, for example, shown by Geweke (1998), the marginal likelihood is directly related to the predictive density function. Predictive performance is a natural criterion for validating models for forecasting and policy analysis.

The marginal likelihood of model i is defined as,

$$m_i = \int_\theta p(\theta|i)p(Y_T|\theta, i)d\theta, \tag{15}$$

where $p(\theta|i)$ is the prior density and $p(Y_T|\theta, i)$ is the likelihood function of the data, Y_T, conditional on model i and parameter vector θ. By integrating out the parameters of the model, the marginal likelihood gives an indication of the overall likelihood given the data.

By specifying our beliefs about alternative models in the form of a prior distribution, we can calculate the posterior probability distribution,

$$\widetilde{p_i} = \frac{p_i m_i}{\sum_j p_j m_j}, \tag{16}$$

where p_i is the prior probability of model i. We use equal weights for different models to be impartial. Similar to the marginal likelihood, the posterior probability compares the models' ability to predict out of sample.

The majority of our industry characteristics are drawn from Compustat. The sample includes 3,224 domestic firms which we aggregate from 4-digit to 2-digit SIC using sales weighted averages.

[4] The details of estimation of the Bayesian probit models via Gibbs sampling can be found in Albert and Chib (1995).

5.1 Inventories

We looked at the industry inventory to sales ratio for all three stages of processing in Table 7. The ratio of raw materials inventory to sales increases the likelihood ratio index (LRI) by almost 25%. It enters significantly positively and has the highest posterior probability at 44.7%.

[Insert Table 7 Here]

Our asymmetric sectors hold \$0.051 of raw materials inventory per dollar of sales. The symmetric sectors hold on average \$0.034. For each penny increase in this ratio, a sector is 16.8% more likely to be asymmetric.

5.2 Oil prices

We obtained data on energy intensity per value of shipments by 2-digit SIC code from the Department of Energy[5] for 1991 and 1994. We analyzed the averages of the 1991 and 1994 figures. This variable is significantly positive, increases the likelihood ratio index by 13%, but it has a posterior probability of under 1%.

5.3 Other production characteristics

5.3.1 Wages

Davis, Haltiwanger and Schuh (1996) observed that high wage industries had smaller gross job flow rates. Their explanation is that higher paid workers are more skilled and may have more industry specific capital that firms would be reluctant to lose.

We find very little relationship between hourly earnings and employment asymmetry. For example, the highest wage nondurable industry, petroleum, is not asymmetric. This is true whether we use the BLS wage series for production workers or measure output per employee. We report the results for latter variable in Table 7. It is not significant, and it has the second lowest posterior probability in the group.

5.3.2 Declining employment trend

Foote (1998) emphasizes that an industry which is facing a declining employment trend is more likely to be impacted by negative shocks. He proposed an (S, s) model in which the variability of job destruction relative to job creation is higher in industries with a negative employment trend.

[5] The data can be obtained from http://www.eia.doe.gov/emeu/mecs/ mecs94/ei/table11.html

Our cross sectional analysis is not supportive of this model. We include as a regressor the percentage change in sector employment from the beginning of the sample to the end. It enters insignificantly. While both groups have declining employment on average, the average decline in the asymmetric sectors is −11.93% versus −16.07% in the symmetric ones. The posterior probability and marginal log likelihood suggest this is not a particularly important characteristic though.

5.3.3 Capital stock and flows

The capital stock to sales ratio in each sector is not significant, and it has a posterior probability of under 1%. We decided to look at capital flows instead and had much better success. We included spending on property, plant and equipment as a ratio of sales and found this entered significantly positively. It was among the three most powerful variables in the cross section, with the second highest posterior probability of 28% and an LRI of 30.4%.

The sectors that are asymmetric spend on average $0.75 per dollar of sales, while the symmetric sectors spend just $0.42. Our regression estimates imply that for each penny increase in this ratio, a sector is 1.7% more likely to be asymmetric.

We measure the differential impact of demand shocks by looking at credit and stock ratings. We looked at Altman's (1968) bankruptcy Z-score[6], and Standard & Poor's long term debt and stock ratings. The Z-score turned out to be the most successful of the three, with the third highest posterior probability of 20.4% and an LRI of 38.2%.

On the Z-score scale, a rating below 1.81 indicates a high probability of bankruptcy in the next two years, a rating above 3.0 indicates a low probability. The asymmetric sectors have a Z-score of 3.37 on average, while the symmetric sectors average 4.73. The significantly negative coefficient of −1.314 implies that firms facing bankruptcy are more likely to be asymmetric.

Compustat captures the company's long term Standard and Poor's debt rating on a scale from 1 to 20 with smaller numbers indicating higher credit quality. Standard & Poor's also rates stocks from A+ to Liquidation, which Compustat records on a numerical scale from 7 to 22, with 99 indicating reorganization.

Credit ratings do not appear to explain the asymmetry across sectors[7]. The average credit

[6] Five factors enter into the Z-score with weights in parentheses: (1) Earnings before taxes $\times$ 3.3; (2) Total assets/ net sales $\times$ 0.999; (3) Market value of equity/ total Liabilities $\times$ 0.6; (4) Working capital (current assets minus current liabilities) $\times$ 1.2; (5) Retained earnings $\times$ 1.4. This is the formula for public companies. Variants exists for privately held firms.

[7] Similarly weak results were found for free cash flow. These results suggest that the credit channel found by Peersman and Smets (2002) may work differently in the U.S. than Europe.

rating across the sectors was a 9.43 or A- on the Standard and Poor's scale. The highest rated sector, chemicals, with an average AA+ credit rating is asymmetric, while tobacco and food, whose A ratings were the third and fourth highest, are not asymmetric. Our lowest rated sector, leather, which is between BB and BB- with an average rating of 14.89 is symmetric, while stone, clay and glass, our third lowest rated at BB- with a score of 12.05, is asymmetric. The coefficient on credit ratings is insignificant in the probit.

Stock ratings might also reflect a differential access to capital, but our results indicate this has little effect on asymmetry with posterior probability of the model under 1%. Our highest rated industry, tobacco, with the top 7.00 rating is asymmetric, but leather, the second highest rated with an above average 9.99, is symmetric.

It appears that balance sheet factors captured by the Z-score do a better job in summarizing the effects of credit availability on asymmetry.

5.4 Total contribution

We combine the three variables with the highest posterior probability into a single regression: raw materials inventory, spending on plant and equipment, both as a ratio to firm sales, and the Z-score. Collectively, these three regressors provide a 67% increase in the likelihood ratio index and correctly classify 85% of the sectors.

6. Conclusion

These results have punctuated the need to focus on industrial sectors, not aggregates, when looking at asymmetry. The evidence at the aggregate level for the U.S. is very mixed.

We find that the aggregate driving forces behind asymmetry can be explained by demand side leading indicators including the term spread and consumer expectations. We find a much smaller role, at the sector level, for either inventories or oil prices, which have received more attention in the literature.

The microeconomics of production helps explain most of the cross section variation among sectors. Sectors with low raw materials inventory to sales ratios, lower plant and equipment expenditures, and lower energy intensity seem better able to smooth these asymmetric driving processes.

At the firm level, balance sheet variables also play a role in asymmetry. Altman's Z-score conveniently summarizes the effect of credit conditions.

This empirical analysis, we hope, is a stepping stone toward a general equilibrium model of business cycle asymmetries. Our results suggest that more attention to the demand side in these models may prove fruitful.

Appendix A:
Description of Triples Test

The triples test is formulated as follows:

$$\frac{\hat{\eta}-\eta}{\sqrt{\hat{\sigma}^2_{\hat{\eta}}/T}} \tag{17}$$

where

$$\begin{aligned}
\hat{\eta} &= \frac{1}{\binom{T}{3}} \sum_{i<j<k} f^*(X_i, X_j, X_k) \\
\hat{\sigma}^2_{\hat{\eta}}/T &= \frac{1}{\binom{T}{3}} \sum_{c=1}^{3} \binom{3}{c} \binom{T-3}{3-c} \hat{\zeta}_c \\
\hat{\zeta}_1 &= \frac{1}{T} \sum_{i=1}^{T} (f_1^*(X_i) - \hat{\eta})^2 \\
\hat{\zeta}_2 &= \frac{1}{\binom{T}{2}} \sum \sum_{j<k} (f_2^*(X_j, X_k) - \hat{\eta})^2 \\
\hat{\zeta}_3 &= \frac{1}{9} - \hat{\eta}^2 \\
f^*(X_i, X_j, X_k) &= \frac{1}{3}[sign(X_i + X_j - 2X_k) + sign(X_i + X_k - 2X_j) \\
&\quad +sign(X_j + X_k - 2X_i)] \\
f_1^*(X_i) &= \frac{1}{\binom{T-1}{2}} \sum \sum_{j<k, i\neq j, i\neq k} f^*(X_i, X_j, X_k) \\
f_2^* &= \frac{1}{T-2} \sum_{i=1, i\neq j\neq k, i\neq k} f^*(X_i, X_j, X_k)
\end{aligned}$$

and $\eta = 0$ is the null hypothesis of no asymmetry. The asymptotic distribution of the test statistic is standard normal.

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TABLE 1
Triples Test for Asymmetry - NIPA Aggregates

	Deepness				Steepness			
	Statistic	SE	t-stat	p-value	Statistic	SE	t-stat	p-value
Gross domestic product	-0.0064	0.0162	-0.3929	0.6944	-0.0112	0.0178	-0.6276	0.5303
Final sales of domestic product	-0.0222	0.0177	-1.2530	0.2102	0.0276	0.0190	1.4489	0.1474
Change in private inventories	0.0059	0.0150	0.3915	0.6954	-0.0166	0.0162	-1.0280	0.3040

NOTES: The test is based on Randles et. al. (1980) and is described in (17). The data are detrended using log differences. The sample period is quarterly 1967:1 to 1997:4.

TABLE 2
Triples Test for Asymmetry - Sales and Inventories

	Deepness				Steepness			
	Sales	FGI	WPI	MI	Sales	FGI	WPI	MI
MANUFACTURING								
DURABLES					**X**			
Lumber								
Furniture								
Stone clay glass	**X**			**X**				
Primary metals	**X**							
Fabricated metals	**X**							
Industrial mach.	**X**					**X**		
Electronic mach.	**X**	**X**				**X**		
Transport equip.					**X**			
Instruments			**X**	**X**				
Other manuf.								
NONDURABLES								
Food								**X**
Tobacco								
Textiles	**X**							
Apparel								
Paper				**X**				
Printing								
Chemicals								
Petroleum								
Rubber								
Leather								

NOTES: FGI is finished goods inventory, WPI is work-in-process inventory, and MI is raw materials inventory. The test is based on Randles et. al. (1980) and is described in (17). The data are detrended using log differences. The sample period is quarterly 1967:1 to 1997:4. An X indicates significance at the 10% level.

TABLE 3
Triples Test for Asymmetry - Oil Price Variables

	Deepness				Steepness			
Series	Statistic	SE	t-stat	p-value	Statistic	SE	t-stat	p-value
Nominal oil (NOP) %ch	0.0221	0.0208	1.0622	0.2881	0.0036	0.0205	0.1739	0.8619
NOP4	**0.1933**	0.0089	21.6582	0.0000	0.0116	0.0266	0.4355	0.6632
NOP12	**0.1766**	0.0114	15.5096	0.0000	0.0001	0.0277	0.0048	0.9962
Real oil %ch	-0.0023	0.0205	-0.1142	0.9091	0.0002	0.0206	0.0115	0.9908
Oil Std.	0.0096	0.0210	0.4552	0.6489	-0.0122	0.0192	-0.6368	0.5243
Oil Std >0	**0.1923**	0.0083	23.2487	0.0000	0.0053	0.0247	0.2135	0.8309
Hamilton Shock	**0.0242**	0.0111	2.1821	0.0291	0.0000	0.0160	0.0000	1.0000

NOTES: The test is based on Randles et. al. (1980) and is described in (17). The oil price data are quarterly from 1967:1 to 1997:4. NOP is the change in the wholesale price of gasoline; NOP4 is the percentage change with respect to the 4 quarter high, and NOP12, the 12 quarter high. Real oil is the nominal price change deflated by the wholesale price deflator. Oil Std standardizes the real oil price by a GARCH(1,1) measure of its volatility. Oil Std >0 is the same process, restricted to only positive shocks. Hamilton Shock is a judgemental series of oil price shocks corresponding to periods of severe shortages. Boldface indicates significance at the 10% level.

TABLE 4
Triples Test for Asymmetry - Leading Indicators

	Deepness				Steepness			
Indicator	Statistic	SE	t-stat	p-value	Statistic	SE	t-stat	p-value
Orders: consumer goods, mtrls.	-0.0201	0.0133	-1.5048	0.1324	-0.0065	0.0147	-0.4445	0.6567
Orders: nondef. capital goods	**0.0307**	0.0123	2.4920	0.0127	**-0.0475**	0.0137	-3.4610	0.0005
Building permits	**-0.0244**	0.0115	-2.1139	0.0345	**-0.0248**	0.0144	-1.7222	0.0850
Real stock prices	0.0157	0.0128	1.2286	0.2192	**-0.0395**	0.0135	-2.9273	0.0034
Real M2	-0.0193	0.0121	-1.6019	0.1092	-0.0102	0.0143	-0.7129	0.4759
Term spread: (10 years - FF)	**-0.0338**	0.0135	-2.5039	0.0123	0.0092	0.0179	0.5164	0.6056
Consumer expectations	**-0.0597**	0.0119	-5.0192	0.0000	0.0032	0.0160	0.1996	0.8418

NOTES: The test is based on Randles et. al. (1980) and is described in (17). The leading indicators are from the Conference Board. Bold indicates significance at the 10% level.

TABLE 5
Markov Switching Tests of Asymmetry - Model without Factors

Sector	Mean	Std. Dev.	Lower HPDI	Upper HPDI
MANUFACTURING	**-0.1715**	0.1034	-0.3309	-0.0068
DURABLES	**-0.1945**	0.1119	-0.3720	-0.0171
Lumber	**-0.2349**	0.1444	-0.4589	-0.0158
Furniture	-0.1728	0.1351	-0.3995	0.0201
Stone clay glass	**-0.2024**	0.1031	-0.3638	-0.0329
Primary metals	**-0.2138**	0.1029	-0.3766	-0.0454
Fabricated metals	**-0.2792**	0.1189	-0.4714	-0.0832
Industrial mach.	-0.1427	0.0984	-0.2988	0.0150
Electronic mach.	**-0.2611**	0.1146	-0.4454	-0.0725
Transport. Eq.	**-0.2446**	0.12934	-0.4466	-0.0262
Instruments	-0.1419	0.1641	-0.4249	0.1227
Other manuf.	-0.2149	0.2010	-0.5798	0.0758
NONDURABLES	**-0.2203**	0.1180	-0.4032	-0.0266
Food	0.0630	0.2699	-0.3317	0.4868
Tobacco	**-0.2295**	0.1330	-0.4303	-0.0068
Textiles	**-0.2314**	0.1107	-0.4134	-0.0575
Apparel	-0.1216	0.2116	-0.4422	0.2744
Paper	-0.1886	0.1198	-0.3701	0.0010
Printing	-0.1402	0.0997	-0.2878	0.0131
Chemical	**-0.1821**	0.1072	-0.3454	-0.0088
Petroleum	-0.0912	0.2515	-0.4846	0.3163
Rubber	**-0.2077**	0.1119	-0.3812	-0.0249
Leather	0.0711	0.2423	-0.3075	0.4634

NOTES: The HPDI is the highest posterior density interval based on a Bayesian estimation of the Markov switching model. We report the test statistic $R_{3,n}$ from (14). Boldface indicates that the 90% HPDI does not include zero.

TABLE 6
Markov Switching Tests of Asymmetry

	None	Inv.	Oil	Orders	Permits	Stocks	Expect	Spread
MANUFACTURING	**X**		**X**	**X**				
DURABLES	**X**	**X**	**X**	**X**				**X**
Lumber	**X**	**X**		**X**	**X**	**X**		
Furniture		**X**						
Stone clay glass	**X**	**X**	**X**	**X**	**X**	**X**		
Primary metals	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**
Fabricated metals	**X**	**X**	**X**	**X**	**X**	**X**	**X**	
Industrial mach.			**X**					**X**
Electronic mach.	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**
Transportation	**X**	**X**	**X**	**X**		**X**		
Instruments								
Other manuf.			**X**	**X**				
NONDURABLES	**X**	**X**	**X**	**X**	**X**			
Food			**X**					
Tobacco	**X**		**X**	**X**	**X**	**X**	**X**	**X**
Textiles	**X**	**X**		**X**				
Apparel								
Paper				**X**			**X**	
Printing								
Chemical	**X**	**X**	**X**	**X**	**X**	**X**		
Petroleum								
Rubber	**X**	**X**	**X**	**X**	**X**	**X**		
Leather								

NOTES: An X indicates presence of the sharpness asymmetry in $R_{3,n}$ from (14) at the 10% level or lower. The test is based on the HPDI of our Bayesian estimation of the Markov switching model. Inv. is raw materials inventories, Oil is the oil shock measure in (6), Orders are new orders for non-defense capital goods, Permits is new building permits for single family homes, Stocks is the return on the S&P 500 index, Expect is consumer expectations from the U. of Michigan, and Spread is the spread between the 10-year bond and the federal funds rate. All factors are lagged one time period.

TABLE 7
Cross Section Analysis of Firm Characteristics

	Post. Prob.	LRI	ME	Pred.%	Beta	SE Beta	HPDI Lower	HPDI Upper
I/S Raw	0.447	0.242	16.781	0.800	**44.268**	21.279	9.352	78.858
PPE/S	0.280	0.304	1.710	0.750	**4.640**	1.940	1.445	7.709
Z-score	0.204	0.382	-0.491	0.750	**-1.314**	0.449	-2.041	-0.565
I/S Work	0.031	0.023	3.666	0.650	9.558	12.684	-11.900	29.689
I/S Finished	0.028	0.049	-4.137	0.550	-10.841	8.969	-25.494	4.076
K/S	0.010	0.061	1.085	0.700	2.833	2.271	-0.956	6.540
Energy	0.001	0.132	0.057	0.700	**0.152**	0.086	0.007	0.291
SP Stock	0.000	0.049	0.049	0.600	0.128	0.106	-0.047	0.296
Credit	0.000	0.003	-0.019	0.500	-0.049	0.135	-0.272	0.173
O/E	0.000	-0.001	-0.002	0.450	-0.004	0.019	-0.034	0.027
%ch N	0.000	0.002	0.001	0.450	0.001	0.007	-0.010	0.012
ISR+PPE+Z		0.674		0.850				

NOTES: The model is a probit regression for whether asymmetry was found in a sector using the Markov switching tests. Bold face indicates that the 90% HPDI does not include zero. Z-score is Altman's (1968) measure, PPE/S is plant and equipment expenditure as a ratio of sales, I/S is inventory to sales for the three stages of processing, Energy is the energy intensity measured by the Dept. of Energy, K/S is the capital stock to sales ratio, Stock Rt. is the S&P stock rating on the company, credit is the S&P long term debt rating, %ch N is the change in employment in the sector between 1967 and 1997, O/E is output per employee. Post. Prob is the Bayesian posterior probability as described in (16), LRI is the likelihood ratio index, ME is the marginal effect is the percentage change in the probability of being asymmetric for a one percent change in the dependent variable, measured at the mean, Pred. % is the percentage of correct classifications, Beta is the coefficient estimate, SE is the standard error, and HPDI is the highest posterior density interval for the coefficient. All the regressions also included a constant term.