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Accounting for the Sources of Macroeconomic Tail Risks

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Abstract

Using a multi-industry real business cycle model, we empirically examine the microeconomic origins of aggregate tail risks. Our model, estimated using industry-level data from 1972 to 2016, indicates that industry-specific shocks account for most of the third and fourth moments of GDP growth.

Keywords: production networks, business cycles, tail risk

JEL codes: D5, E2, E3

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1 Introduction

Aggregate activity exhibits tail risks. That is, the distribution of aggregate fluctuations has fatter tails than that of a normally distributed random variable. Understanding these tail risks is important for multiple macroeconomic topics, including evaluating the utility cost of macroeconomic fluctuations (Barro, 2009) and forecasting aggregate activity (Curdia, Del Negro, and Greenwald, 2014). In this paper, we empirically investigate whether higher moments have sectoral origins.

We begin by exploring the skewness and kurtosis of GDP and industries' output growth rates. As we document, GDP growth exhibits positive excess kurtosis of 2.34.[1] Moreover, for most of the industries in our sample, output growth is kurtotic. There are, however, substantial differences across industries in the extent to which their output growth rate distributions deviate from normality.

We apply the structural approach of Foerster, Sarte, and Watson (2011) to filter the underlying productivity shocks from data on industries' output growth rates. With these productivity shocks, we evaluate the contribution of industry-specific shocks to aggregate fluctuations' departures from normality: We first compute the model-implied higher moments of GDP with both common and industry-specific shocks and then with industry-specific shocks only. Our main finding from this exercise is that the importance of industry-specific shocks depends on the assumed complementarity of inputs in sectoral production functions. For values of complementarity estimated in Atalay (2017), industry-specific shocks account for the predominant share of the third and fourth moments of GDP fluctuations.

Our work contributes first to the literature, initiated by Long and Plosser (1983), that hypothesizes that localized disturbances shape aggregate fluctuations. Within this literature, our paper is closest to Foerster, Sarte and Watson (2011) and Atalay (2017). Like these papers, we apply a general equilibrium multi-industry model to recover the productivity shocks experienced by each industry, and then extract the common component of our recovered productivity shocks. We contribute to this literature by assessing the role of industry-specific shocks in generating deviations from normality in GDP growth.

Second, our paper contributes to the literature on the micro sources of macroeconomic tail risks. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017) provide necessary and sufficient conditions for idiosyncratic, industry-specific productivity shocks to engender macroeconomic tail risk even as the number of industries becomes exceedingly large. In a model in which industries' production functions exhibit complementarities across inputs and de-

[1] To put this in context, the excess kurtosis of the Laplace (double exponential) distribution equals 3, that of the normal distribution is zero.

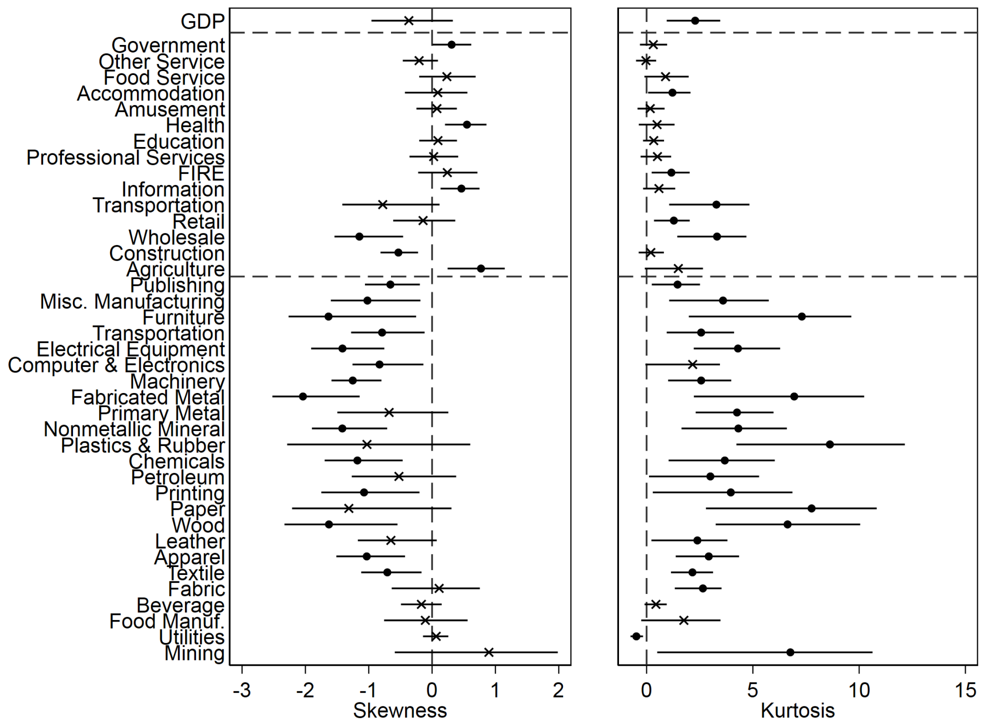

Figure 1: The two panels give the skewness (left panel) and excess kurtosis (right panel) of quarterly output growth, with corresponding 90 percent confidence intervals (computed from 1000 bootstrapped samples). A filled in circle indicates that the estimate is statistically different from zero (at 10 percent significance); an "x" indicates no significance.

creasing returns to scale, Baqaee and Farhi (2017) demonstrate that GDP growth can be fat-tailed even with thin-tailed productivity shocks. Compared to these two papers, our contribution is to empirically recover the distribution of fundamental shocks, then establish whether the common component of these micro shocks generates aggregate tail risk.

2 Data

Figure 1 presents the skewness and kurtosis of growth rates of GDP and of individual sectors' gross output. These growth rates are at the quarterly frequency, computed using data from the Federal Reserve Board (for goods-producing industries) and the Bureau of Economic Analysis (for all other industries) from 1972 to 2016.[2]

GDP growth exhibits tail risk: Over the sample period, the excess kurtosis of GDP

[2]For industries outside the Federal Reserve Board data set, industry output is measured at the annual frequency. We impute quarterly growth rates at the industry level to match the industry's annual output growth and the quarterly growth rate of non-industrial production.

growth is 2.34, with a bootstrapped 90 percent confidence interval of 0.95 to 3.53.[3] GDP growth is also slightly negatively skewed, but not statistically significantly so. These statistics are depicted in the first rows of the two panels of Figure 1. In the remaining rows, we present the output growth rates of the 39 constituent industries in our data set. Among these industries, output growth rates are significantly negatively skewed for 16 industries, significantly positively kurtotic for 25 industries, with many of these industries concentrated within durable goods manufacturing.

Figure 1 singles out certain industries as potential sources of aggregate tail risk. However, since input-output linkages and general equilibrium effects may lead shocks in one industry to manifest as output fluctuations in another, we have yet to determine the extent to which individual industries contribute to the GDP tail risk that we have documented in Figure 1. We turn to this task in the following section.

3 Model

The model broadly follows that in Foerster, Sarte, and Watson (2011) and Atalay (2017). The aim of this model is to recover industries' productivity shocks from data on industry output. The economy consists of N perfectly competitive industries and a representative consumer.

The consumer supplies labor (L_t) and consumes the goods and services (C_{tJ}) produced by each industry:

$$U_0 = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \log C_t - \frac{\phi}{\phi+1} L_t^{\frac{\phi+1}{\phi}} \right\}, \text{ where } C_t = \prod_{J=1}^{N} \left(\frac{C_{tJ}}{\xi_J} \right)^{\xi_J}. \tag{1}$$

In equation 1, ξ_J represents the importance of the industry J good in the consumer's preferences, and ϕ the labor supply elasticity.

[3] We begin the sample in 1972, coinciding with the date at which the Federal Reserve Board Industrial Production begins measuring output of individual goods-producing industries. Using annual data from 1929 to 2016 the excess kurtosis of GDP growth equals 3.29, with a 90% confidence interval of (1.51, 5.26).

The production function of industry J is given by:

$$Q_{tJ} = A_{tJ} \cdot \left(\frac{K_{tJ}}{\alpha_J}\right)^{\alpha_J} \cdot \left(\frac{L_{tJ}}{1-\alpha_J-\mu_J}\right)^{1-\alpha_J-\mu_J} \cdot \left(\frac{M_{tJ}}{\mu_J}\right)^{\mu_J}, \text{ where} \tag{2}$$

$$M_{tJ} = \left[\sum_{I=1}^{N} \left(\Gamma_{IJ}^{M}\right)^{\frac{1}{\varepsilon}} \left(M_{t,I\to J}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\varepsilon/(\varepsilon-1)}, \text{ and} \tag{3}$$

$$K_{t+1,J} = (1-\delta)\cdot K_{tJ} + \prod_{I=1}^{N}\left(\frac{X_{t,I\to J}}{\Gamma_{IJ}^{X}}\right)^{\Gamma_{IJ}^{X}}. \tag{4}$$

Output is produced with capital, labor, and intermediate inputs (with cost shares α_J, $1-\alpha_J-\mu_J$, and μ_J, respectively). Here, A_{tJ} characterizes industry J's exogeneous productivity at time t (equation 2). The intermediate input bundle is a CES composite of materials purchased from other industries (equation 3). Capital is industry-specific, depreciates at a common rate δ, and is augmented through investment goods purchased from other industries (equation 4).

Each industry's output can either be consumed or purchased by other industries:

$$Q_{tJ} = C_{tJ} + \sum_{I=1}^{N} X_{t,J\to I} + M_{t,J\to I}. \tag{5}$$

Total labor supply equals the sum of all labor demanded by the N industries:

$$L_t = \sum_{J=1}^{N} L_{tJ}. \tag{6}$$

Finally, productivity follows a geometric random walk:

$$\log \mathbf{A}_t = \log \mathbf{A}_{t-1} + \omega_t, \tag{7}$$

where $\mathbf{A}_t \equiv (A_{t1}, ...A_{tN})'$, and ω_t is a zero-mean i.i.d. random vector.

We focus on a competitive equilibrium of the economy characterized by equations 1 through 7. As shown in Foerster, Sarte, and Watson (2011), in the competitive equilibrium output growth evolves according to:

$$\Delta \log \mathbf{Q}_{t+1} = \Pi_1 \cdot \Delta \log \mathbf{Q}_t + \Pi_2 \cdot \omega_t + \Pi_3 \cdot \omega_{t+1}, \tag{8}$$

up to a first-order approximation.[4] In equation 8, $\mathbf{Q}_t \equiv (Q_{t1}, ...Q_{tN})'$, and Π_1, Π_2, and

[4] See Online Appendix F of Atalay (2017) for the derivation of equation 8.

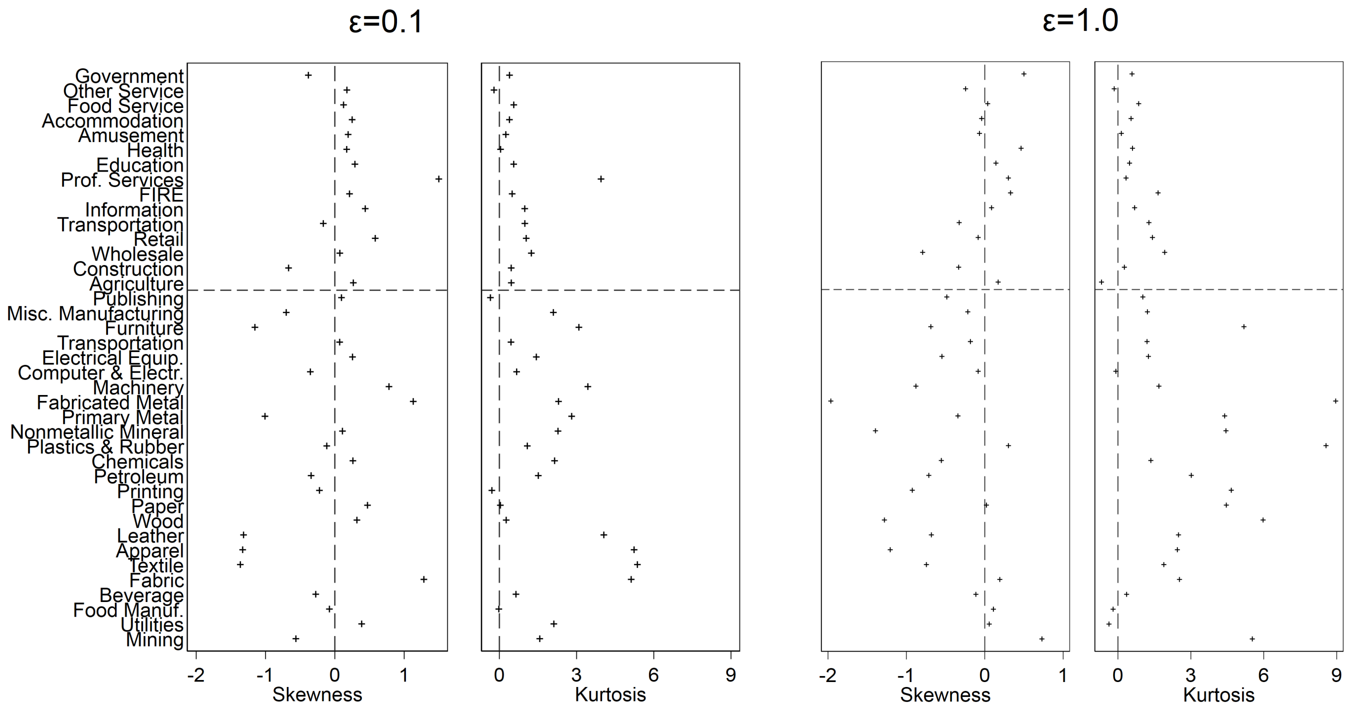

Figure 2: Each panel gives the skewness and excess kurtosis of the ω_{tJ}. The left two panels use $\varepsilon = 0.1$; the right two panels use $\varepsilon = 1.0$.

Π_3 are matrices whose elements are functions of the parameters of the model.

We calibrate the model following Atalay (2017): We set $\phi = 2$, $\beta = 0.99$, and $\delta = 0.025$. We compute α_J, ξ_J, μ_J, Γ^M_{IJ}, and Γ^X_{IJ} from the 1997 BEA Industry Economic Accounts.[5] Finally, we take a range of values of ε, from 0.1 to 1.0. The lower end of this interval is taken from Atalay (2017), while the upper end is the calibrated value in Foerster, Sarte, and Watson (2011), among others.

Using our industry-level data from 1972 to 2016, we retrieve industry×quarter-level productivity shocks, ω_{tJ}, from a Kalman-filter application of equation 8. As an analogue to Figure 1, Figure 2 plots the skewness and kurtosis of the ω_{tJ}. For both $\varepsilon = 0.1$ and $\varepsilon = 1.0$, the recovered productivity shocks have positive kurtosis, consistent with one of the necessary conditions of Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017). However, the shocks may share a common component and thus violate the independence assumption in Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017). We now investigate this possibility.[6]

[5] Proxying for within-industry repair and maintenance expenditures (McGrattan and Schmitz, 1999), we add 0.35 to the diagonal elements of Γ^X.

[6] As Baqaee and Farhi (2017) emphasize, since we approximate our model log-linearly, it is a priori conceivable that the distribution of filtered productivity shocks (absent such an approximation) would more closely resemble that of a normal random variable. However, the calibration in Baqaee and Farhi (2017) also

4 Results and Discussion

With the estimates of ω_{tJ}, we perform two exercises to evaluate the industry-specific contribution of aggregate tail risk.

First, Foerster, Sarte, and Watson (2011) and Atalay (2017) compute the average pairwise correlation of ω to summarize the importance of the common component of productivity shocks. Building off of this idea, we measure the higher-order analogue of the pairwise correlation: the co-skewness and co-kurtosis. Using μ_{ω_X} and σ_{ω_X} to denote the mean and standard deviation of productivity shocks in industry X, we define the co-skewness of productivity shocks in industries H, I, and J as:

$$\hat{\rho}_3\left(\omega_H, \omega_I, \omega_J\right) = \frac{\rho_3\left(\omega_H, \omega_I, \omega_J\right)}{\sigma_{\omega_H} \cdot \sigma_{\omega_I} \cdot \sigma_{\omega_J}}, \text{ where} \tag{9}$$

$$\rho_3\left(\omega_H, \omega_I, \omega_J\right) = \mathbb{E}\left[\left(\omega_H - \mu_{\omega_H}\right) \cdot \left(\omega_I - \mu_{\omega_I}\right) \cdot \left(\omega_J - \mu_{\omega_J}\right)\right], \tag{10}$$

and the co-kurtosis as:

$$\hat{\rho}_4\left(\omega_L, \omega_H, \omega_I, \omega_J\right) = \frac{\rho_4\left(\omega_L, \omega_H, \omega_I, \omega_J\right)}{\sigma_{\omega_G} \cdot \sigma_{\omega_H} \cdot \sigma_{\omega_I} \cdot \sigma_{\omega_J}}, \text{ where} \tag{11}$$

$$\rho_4\left(\omega_L, \omega_H, \omega_I, \omega_J\right) = \mathbb{E}\left[\left(\omega_G - \mu_{\omega_G}\right) \cdot \left(\omega_H - \mu_{\omega_H}\right) \cdot \left(\omega_I - \mu_{\omega_I}\right) \cdot \left(\omega_J - \mu_{\omega_J}\right)\right]. \tag{12}$$

The left panel of Figure 3 plots the average pairwise correlation, co-skewness, and co-kurtosis. Consistent with Atalay (2017), productivity shocks are less correlated with one another when ε is small. Similarly, the average co-skewness and co-kurtosis are closer to zero with relatively low values of ε, suggesting a stronger role for industry-specific shocks for higher-moment GDP fluctuations under this parameterization.

Our second exercise consists of principal component analysis and its higher order analogue: moment component analysis (see Jondeau, Jurczenko, and Rockinger, 2017.) The principal component analysis procedure that we perform partitions the productivity shocks' covariance matrix into two components: a rank-one matrix representing the contribution of common shocks, and a diagonal matrix representing the contribution of industry-specific shocks. With these two covariance matrices in hand, we compute the model-implied covariance matrices for industries' value added that results only from sector-specific shocks or from both sector-specific and common shocks. We then compute the fraction of aggregate output volatility that is explained by the independent component of industries' productivity shocks; see equation 17 of Atalay (2017).

indicates that — for our calibrated value of ε — the first-order approximation is fairly accurate so long as inputs can be freely re-allocated across sectors, as is the case in our setup.

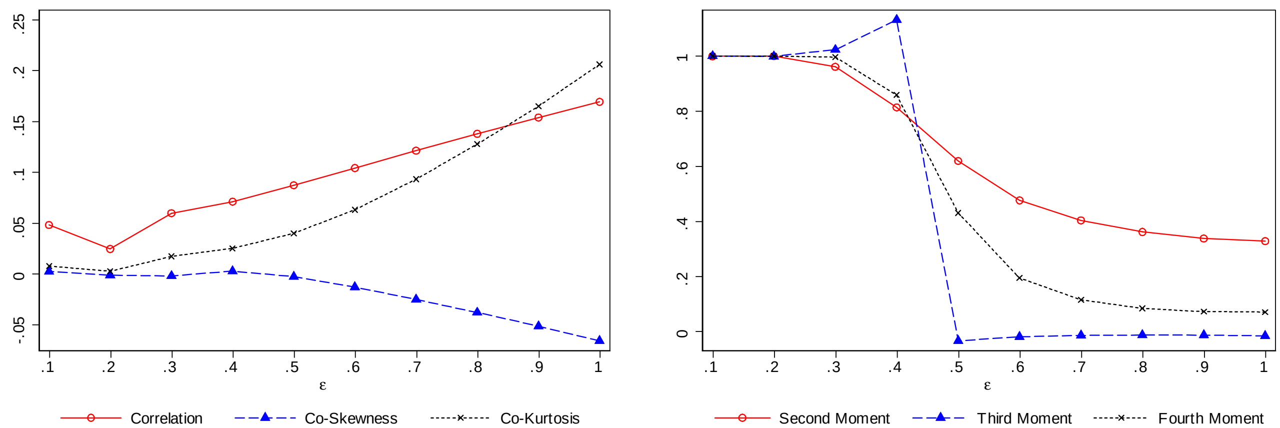

Figure 3: The left panel gives the correlation, co-skewness, and co-kurtosis of ω, with the latter two statistics defined by equations 9 and 11. The right panel gives the share of the second, third, and fourth moments of GDP growth which are induced by industry-specific shocks.

While principal component analysis extracts the first eigenvector — corresponding to the largest eigenvalue — of the covariance matrix, moment component analysis extracts the first eigenvector from the co-skewness and co-kurtosis tensors. To recover the contribution of industry-specific shocks to aggregate skewness, we begin by performing the singular value decomposition of the $N \times N \times N$ dimensional tensor containing the third-order central co-moments $\rho_3(\omega_H, \omega_I, \omega_J)$. We retrieve the tensors associated with the common factor and with industry-specific shocks. We then compute the ratio of the third-moment of GDP growth that is due to industry-specific shocks only and that which is due to both industry-specific and common shocks. We perform a corresponding procedure to assess the contribution of industry-specific shocks to the fourth moment of GDP fluctuations.

The right panel of Figure 3 contains the result of this exercise. As with Foerster, Sarte, and Watson (2011) and Atalay (2017), industry-specific shocks account for less than half of aggregate volatility when $\varepsilon \approx 1$, and a substantially larger portion with smaller values of ε. The new results in this figure relate to the share of the third and fourth moment of GDP fluctuations which are due to sectoral shocks. With a Cobb-Douglas production function, sectoral shocks account for approximately 7 percent of the fourth moment of GDP fluctuations and essentially none of the third moment of GDP fluctuations. With lower elasticities of substitution, sectoral shocks are the primary source of tail risk.

These results extend and reinforce those in Atalay (2017). Using data on industries' input choices and input prices, that paper estimates that industries have limited ability to substitute across their inputs in the short run. Since complementarity in sectoral production functions induces co-movement in industries' output, that earlier paper indicates that shocks specific to individual industries are responsible for a large portion of aggregate volatility. This same logic applies when assessing the role of industry-specific shocks in contributing to higher moments of the distribution of GDP growth. Complementarity in production leads (exceptionally large) shocks in individual industries to induce large shifts in the industries upstream and downstream of the shocked industry. This co-movement of exceptionally large output shifts across industries then manifests as large GDP fluctuations.

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