Aggregate Fluctuations from Clustered Micro Shocks

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Abstract

Idiosyncratic shocks to individual firms affect aggregates when they are correlated. In this case, a firm's cross-sectionally demeaned fluctuations (a) are a poor proxy for measuring true idiosyncratic shocks and (b) have negligible cross-firm correlation by construction, regardless of true correlation. This paper proposes a way to calculate a range of the contribution of idiosyncratic comovements across firms within industries to aggregate fluctuations, "clustered origins", from observed data. In the US, clustered origins can explain GDP volatility and its evolution. The contribution of clustered origins to GDP volatility increased from around 10% to 25% over the past two decades. These findings suggest networks and interconnections between firms deserve a central place in macroeconomics.

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1. Introduction

Can idiosyncratic micro shocks to individual firms drive sectoral or economy-wide fluctuations? When there are numerous firms, negative shocks to some firms offset positive shocks to others, and vice versa. Thus, idiosyncratic shocks cannot affect aggregates. However, this averaging out argument collapses if the idiosyncratic shocks correlate across firms. The shocks comove leading to short-run departures from their long-run level (average). The averaging out argument also fails in the presence of extremely large firms. Idiosyncratic shocks to these firms do not disappear in aggregation. Pairwise correlated idiosyncratic shocks and the presence of mega-size firms allow macro fluctuations can arise from micro shocks.

Micro origins of macro volatility have received increasing interest in recent years.[1] Starting with the seminal work of Jovanovic (1987) and Gabaix (2011), important literature investigates "granularity" how micro shocks generate macro fluctuations when the firm size distribution is fat-tailed (e.g., di Givonanni and Levchenko, 2012, Carvalho and Gabaix, 2013, Carvalho, 2014, among many others). Compared with these studies, there is currently a lack of research on the role of another second moment, pairwise correlation across firms, in the business cycle.

This paper attempts to offer an additional microfoundation for aggregate shocks in the business cycle literature by proposing and implementing a way to quantify the aggregate volatility derived from cross-firm comovements of idiosyncratic shocks within an industry, referred to as "clustered origins". The evolution of US GDP volatility can increasingly be accounted for by clustered origins. These findings indicate the importance of a growing literature on networks and interactions between firms in macroeconomics.

To measure clustered origins, I begin with a simple and flexible framework where a firm's business cycle component of productivity or sales consists of a common and idiosyncratic shocks that are additively separable and uncorrelated. The common and idiosyncratic shocks are not directly observable. One easy and widely used way to identify common

[1] For example, Comin and Philippon (2005), Comin and Mulani (2006), Carvalho and Gabaix (2013), and many others study the evolution of firm- and aggregate-level volatility as well as their relationships.

and idiosyncratic shocks is by cross-sectionally demeaning variables. Unfortunately, this method does not work well when idiosyncratic shocks are mutually dependent.

When there exists pairwise correlation of idiosyncratic shocks, a cross-sectional sample mean of firm fluctuations and deviations from it are a poor proxy for a common and idiosyncratic shocks, respectively. The sample mean and demeaned fluctuations do not converge to the true shocks in mean square. Notably, their average cross-firm correlation is asymptotically zero by construction, regardless of true idiosyncratic shocks' correlation. Also, a firm's demeaned fluctuations correlate with the sample mean even if its true idiosyncratic shock is independent of the common shock. Thus, the sample mean and deviations from it tend to ignore clustered origins, by construction. Consequently, I need to recover the true common and idiosyncratic shocks and compute their variance and covariance in order to get a correct understanding of the business cycle and its micro origins.

I introduce a simple tool that allows us to organize the micro-foundations of the business cycle volatility both quantitatively and systematically. Instead of estimating a point value of firms' common and idiosyncratic shocks' variance and covariance, I compute their upper- and lower-bounds from the observed variance and covariance of firm's business cycle fluctuations for each industry. The method relies on two basic statistical facts from Cauchy–Schwarz inequality: (1) variances are non-negative, and (2) correlation coefficients lie between negative and positive one. The next step is to aggregate the idiosyncratic shocks' variance and covariance ranges with sales weights in each industry to compute the ranges of industry-level clustered and granular origins, respectively. Then, I aggregate the industries' ranges of micro origins in the whole economy with adjusting for the Domar weight. The main advantage is that my approach avoids misspecification issues after measuring an individual firm's business cycle components.

Using panel data on publicly traded firms in the US economy, I compute the evolution of clustered and granular origins of aggregate fluctuations based on business cycle components of labor productivity.[2] Both micro origins are essential to understand "great modera-

[2]As an alternative, I also consider business cycle components of real sales. The choice of business cycle components does not affect my main results.

tion". After the early 1980s recession, the micro origins contribute to the decline of the US GDP volatility. Also, the recent rise of the GDP volatility in the 21st century is associated with two types of micro origins, especially the clustered origins. In the early 2000s, the clustered origins' ratio to the GDP volatility was below 10%; however, it increased to 20% in recent times. These results contribute to the literature on the great moderation, for example, Kim and Nelson (1999), Stock and Watson (2002), Comin and Mulani (2006), Davis, Haltiwanger, Jarmin, Miranda, Foote and Nagypal (2006), and many others. My findings closely relate to the results of Carvalho and Gabaix (2013) in which the fundamental volatility — sectoral or firm-level shocks' volatility — account for the great moderation.

This paper's work complements recent efforts in the literature on micro origins of macro fluctuations, in particular granularity introduced by Gabaix (2011).[3] Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012), Carvalho (2014), Oberfield (2018), Herskovic, Kelly, Lustig and Van Nieuwerburgh (2020) and many others have investigated network origins. Networks (supply chains and input-output linkages) shape the size distribution or/and firm volatility, amplifying the granular origins. Carvalho and Gabaix (2013), di Giovanni, Levchenko and Mejean (2014) consider cross-sector correlations and correlation of the shocks from different levels of aggregation. di Givonanni and Levchenko (2012), di Giovanni, Levchenko and Mejean (2014), Gaubert and Itoskhoki (2018) study micro origins of business cycle fluctuations in an open economy context. In contrast to these studies, my paper focuses on correlated idiosyncratic shocks across firms within a cluster itself. Correlated idiosyncratic shocks across firms at the industry and national level are an additional source of the aggregate business cycle.

Besides granular origins, I introduce clustered origins by relaxing the zero cross-firm correlation assumption. This is a key contribution of this paper to the existing literature. Predominantly, macroeconomics has assumed zero pairwise correlation across firms' idiosyncratic shocks and thus ignored clustered origins. As I discussed, the average pairwise correlations of deviations from the sample mean is asymptotically zero. Thus, the newly de-

[3] See in particular, but not only, Buch and Neugebauer (2011), Amiti and Weinstein (2018), Bremus, Buch, Russ and Schnitzer (2018) for granular issues related to financial sectors.

fined shocks from the cross-sectional mean yield that the aggregate business cycle volatility comprises the macro and granular origins with negligible clustered origins, by construction.

Zero correlation assumption can rationalize this assumption and result when the cross-sectional sample mean and deviations from the mean can be used as a newly defined common and idiosyncratic shocks. The next step is to answer the question of what condition makes the sample mean and deviations to be well-defined common and idiosyncratic shocks. An individual firm's demeaned fluctuations are always uncorrelated with the mean when variance and covariance of idiosyncratic shocks are identical across firms. In this case, constructing newly defined shocks by demeaning is appropriate.

However, this rationalization relying on identical variance-covariance assumption cannot be applied to the US economy. Not surprisingly, the US firms' business cycle fluctuations and their idiosyncratic shoks have significant cross-firm heterogeneity in their statistical moments, including variance and covariance, even within a narrowly defined industry. A wide range of literature has documented evidence casting doubt on identical variance or/and covariance of idiosyncratic productivity, output, and financial performance (e.g., Stanley, Amaral, Buldyrev, Havlin, Leschhorn, Maass, Salinger and Stanley, 1996, Xu and Malkiel, 2003, Comin and Philippon, 2005, Comin and Mulani, 2006, Chun, Kim, Morck and Yeung, 2008, Castro, Clementi and Lee, 2015, Tweedle, 2018, Kalnina and Tewou, 2020). Under heterogeneous variance and covariance structure across firms, a cross-sectional sample mean and deviations from it are (1) a poor measure of the common and idiosyncratic shocks and (2) not well-defined macro and micro shocks because they correlate. Researchers need to be careful using cross-sectionally demeaned variables and imposing zero pairwise correlation in order to get a better understanding of the business cycle and its origins.

This paper complements the literature addressing the sectoral origins of macro fluctuations, starting with the seminal research of Long and Plosser (1983). Even if there exist numerous disaggregated sectors, sectoral comovements (arising from supply chains) prevent sector specific shocks from being diversified. This generates substantial aggregate fluctuations. See Bak, Chen, Scheinkman and Woodford (1993), Horvath (1998), Dupor (1999), Foerster, Sarte and Watson (2011), Atalay (2017), among many others. These studies on between-industry comovements and propagations of sectoral shocks are complementary to my works on within-industry comovements at the firm level in the business cycle research.

The rest of the paper is organized as follows. Section 2 illustrates the main idea and motivation. Section 3 shows that the sample mean and variance are a poor proxy for shocks in the presence of pairwise correlation of idiosyncratic shocks. Section 4 demonstrates how to quantify clustered and granular origins from data without demeaning. Section 5 presents data, measurements, and their statistics. Section 6 explores the evolution of clustered and granular origins in the US economy. Section 7 provides an alternative interpretation of the previous sections' results based on a factor model widely used in macroeconometrics. Section 8 concludes.

2. Framework and Motivation

This section introduces a framework with clustered micro shocks to illustrate the basic ideas and motivation. In a cluster, there are N_t firms. Let y_{it} and $\hat{y}_{it}$ denote firm i's variable (e.g., productivity, sales, output, employment, and so on) in the log and its fluctuation (i.e., its business cycle component), respectively. Firm i's fluctuations come from two uncorrelated random variables with zero mean:

$$\hat{y}_{it} = \varepsilon_{\mathrm{A},t} + \varepsilon_{\mathrm{F},it}, \tag{1}$$

where $\varepsilon_{\mathrm{A},t}$ and $\varepsilon_{\mathrm{F},it}$ are the (true) common and idiosyncratic shocks, and their standard deviations are $\sigma_{\mathrm{A},t}$ and $\sigma_{\mathrm{F},it}$, respectively. I allow the pairwise correlation of idiosyncratic shocks between firms i and i' to be non-zero: $\rho_{\mathrm{FF},ii't} \in (-1, 1)$ for $i \neq i'$. In addition to the common shock, the correlated idiosyncratic shock can lead to aggregate-level movements as well as comovements across firms in the cluster.[4] This is why I use the terminology "cluster" instead of "industry", emphasizing pairwise correlations within industries. For convenience, Sections 2 and 3 focus on within a cluster. After Section 4, the whole economy will consist of many clusters.

[4] The pairwise correlation can lead aggregates to short-run departure from the long-run level, i.e., $N_t^{-1} \sum_i \hat{y}_{it} \neq 0$ or $\sum_i w_{it}\hat{y}_{it} \neq 0$. It, however, does not affect the long-run level, i.e., $\mathbb{E}[\hat{y}_{it}] = 0$.

The aggregate volatility comes from the volatility of common and idiosyncratic shocks as well as the pairwise correlation of idiosyncratic shocks. The aggregate business cycle component is the weighted sum of $\hat{y}_{it}$:

$$\hat{Y}_t = \sum_i w_{it}\hat{y}_{it}, \tag{2}$$

where w_{it} is the within-cluster share of firm size and satisfies $\sum_i w_{it} = 1$.[5] Denote its standard deviation by $\sigma^2_{\hat{Y},t}$:

$$\sigma^2_{\hat{Y},t} = \sigma^2_{\mathrm{A},t} + \sum_i w^2_{it}\sigma^2_{\mathrm{F},it} + \sum_i w_{it}\sum_{i'\neq i} w_{i't}\rho_{\mathrm{FF},ii't}\sigma_{\mathrm{F},it}\sigma_{\mathrm{F},i't}, \tag{3}$$

in which the second and third terms are micro origins of macro fluctuations through the volatility and comovements of idiosyncratic shocks, respectively. Define macro, granular, and clustered origins as

Definition 1—Macro origins: $\sigma^2_{\mathrm{A},t}$.

Definition 2—Granular origins: $\Gamma_t = \sum_i w^2_{it}\sigma^2_{\mathrm{F},it}$.

Definition 3—Clustered origins: $\chi_t = \sum_i w_{it}\sum_{i'\neq i} w_{i't}\rho_{\mathrm{FF},ii't}\sigma_{\mathrm{F},it}\sigma_{\mathrm{F},i't}$.

To illustrate the core idea, consider a simple economy where all firms are ex-ante identical, i.e., the variance and covariance of idiosyncratic shocks are identical across firms. Then, equation (3) can be rewritten as follows.

$$\sigma^2_{\hat{Y},t} = \sigma^2_{\mathrm{A},t} + h^2_t\sigma^2_{\mathrm{F},t} + (1-h^2_t)\rho_{\mathrm{F},t}\sigma^2_{\mathrm{F},t}, \tag{4}$$

where $h_t = (\sum_i w^2_{it})^{1/2}$ is the Herfindahl–Hirschman index (HHI) within cluster. There exist micro origins as a convex combination of variance and covariance ($\sigma^2_{\mathrm{F},t}$ and $\rho_{\mathrm{F},t}\sigma^2_{\mathrm{F},t}$) with weight h^2_t. The second term represents granular origins. Lucas (1977) argues that this term is negligible because of diversification: $h_t \to 0$ as $N_t \to \infty$. Thus, the aggregate

[5] The business cycle research uses the Domar weight (Domar, 1961, Hulten, 1978). Sections 4 will consider this issue.

shock mainly derives the business cycle. Gabaix (2011), however, shows that a fat-tailed distribution of firms causes HHI not to converge to zero as the number of firms goes to infinity, which is empirically supported. In that case, idiosyncratic shocks are not diversified and contribute to macroeconomic fluctuations.

This paper focuses on the last term in equation (4) called clustered origins. Aggregate volatility increases when idiosyncratic shocks are positively correlated across firms, $\rho_{\mathrm{F},t} > 0$. The clustered origins decrease with concentration (HHI) in contrast to the granular origins. To illustrate how the clustered origins can be important in macro fluctuations, consider a ratio of the clustered origins to the granular origins. From equation (4), the ratio is

$$\frac{\chi_t}{\Gamma_t} = \left(\frac{1}{h_t^2} - 1\right)\rho_{\mathrm{F},t}, \tag{5}$$

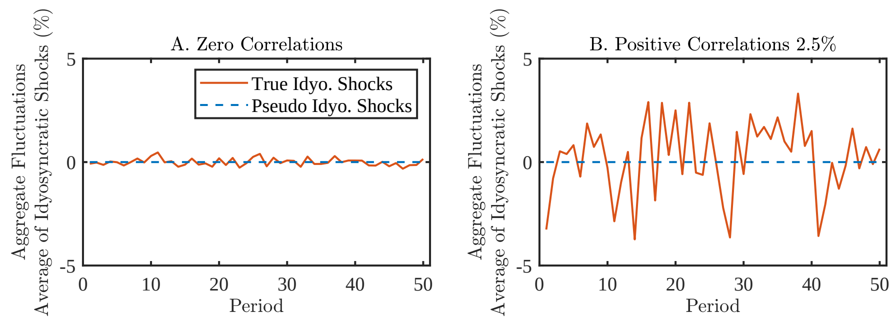
when all firms have the same variance and covariance of idiosyncratic factors. As in Gabaix (2011)'s example, set a size distribution to have $h_t = 0.12$.[6] Small positive pairwise correlations from 1% to 5% imply that the range of cluster origins is between 68% and 342% of granular origins from equation (5). A 1.46% correlation coefficient results in an equal contribution of idiosyncratic comovements across firms and granularity to aggregate volatility. These simple exercises show that the clustered origins potentially contribute to a sizable part of aggregate business cycle fluctuations.

3. Unpleasant Properties of the Sample Mean and Deviations from It

In equation (1), a firm's business cycle component is observable, but its true common and idiosyncratic shocks are not. Many previous business cycle studies use a cross-sectional sample mean as a proxy for the common shock and measure the idiosyncratic shocks by demeaning observations. Define the pseudo common and idiosyncratic shocks by the cross-sectional sample mean and the deviations from it, and denote them by $e_{\mathrm{A},t}$ and $e_{\mathrm{F},it}$, re-

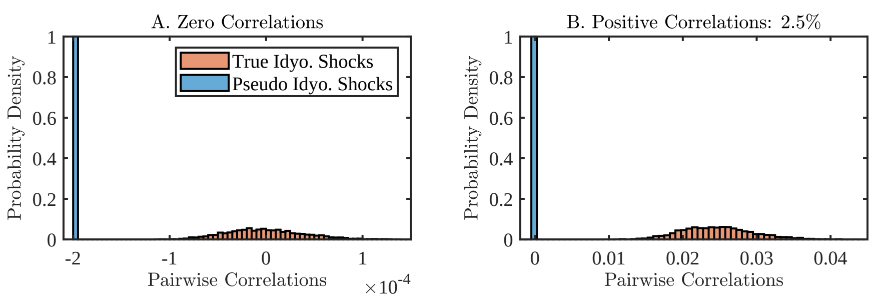
[6] In my US public firm-level data, h_t is around 0.085. In that case, 1% correlation implies clustered origins are around 137% of granular origins in equation (5).

Figure 1. True vs Pseudo Idiosyncratic Shocks and Their Aggregate Fluctuations[a]



[a]The figure plots the aggregate fluctuations based on the average true pseudo idiosyncratic shocks in each period (orange solid line, $N_t^{-1}\sum_{i=1}^{5,000}\varepsilon_{\mathrm{F},it}$, and blue dashed line, $N_t^{-1}\sum_{i=1}^{5,000}e_{\mathrm{F},it}$, respectively.

Figure 2. Sample Pairwise Correlations: True vs Pseudo Idiosyncratic Shocks[a]



[a] The figure plots histograms for sample correlations of true and pseudo variables (orange bars, $\mathsf{corr}(\varepsilon_{\mathrm{F},it},\varepsilon_{\mathrm{F},i't})$, and blue bars, $\mathsf{corr}(e_{\mathrm{F},it},e_{\mathrm{F},i't})$, respectively) from 3,000 simulations.

spectively.

$$\hat{y}_{it} = \left(\bar{\hat{y}}_t\right) + \left(\hat{y}_{it} - \bar{\hat{y}}_t\right) \equiv e_{\mathrm{A},t} + e_{\mathrm{F},it}, \tag{6}$$

where $\bar{\hat{y}}_t = N_t{}^{-1}\sum_i \hat{y}_{it}$ denotes the cross-sectional sample mean.

3.1. A Simple Simulation Exercise

The reason I call the sample mean and deviations from it "pseudo" is that they can obfuscate the origins of business cycle fluctuations when idiosyncratic shocks correlate with each other. Figures 1 and 2 provide a simple example of this. I randomly generate 5,000 firms' true idiosyncratic shocks during 50 periods from a multi-normal distribution with mean zero and 12% standard deviation for two cases: zero or 2.5% correlation.[7] To focus on pairwise correlations, a firm's share is identical across firms, and there is no common shock, $\varepsilon_{\mathrm{A},t} = 0$. Also, I redo this exercise 3,000 times and calculate the sample statistics of true and pseudo idiosyncratic shocks.

Figure 1' Panels A and B plot the aggregate fluctuations of two economies with zero and positive correlations based on the true and pseudo shocks, respectively. The average true idiosyncratic shocks with positive correlation (orange solid line in Panel B) fluctuate more than that with zero correlation (orange solid line in Panel A). However, the average pseudo idiosyncratic shocks (blue dashed line, i.e., firms' demeaned fluctuations) are zero by construction, as shown in Panels A and B.

Figure 2 reports the sample correlations of zero and 2.5% correlation cases based on 3,000 simulations. In Panel B, the pseudo idiosyncratic shocks have almost zero (slightly negative) sample pairwise correlations regardless of true shocks' positive correlations, 2.5%. The figures indicate that positive comovements potentially generate the aggregate business cycle, which can be ignored when I use the deviations from the sample mean.

3.2. Non-Negligible Difference between True and Pseudo Variables

When the true idiosyncratic shocks move together, the pseudo shocks are a poor proxy for the true shocks. Consider the absolute value of difference between true and pseudo shocks:

$$\left|e_{\mathrm{A},t} - \varepsilon_{\mathrm{A},t}\right| = \left|e_{\mathrm{F},it} - \varepsilon_{\mathrm{F},it}\right| = \overline{\varepsilon}_{\mathrm{F},t}, \tag{7}$$

where $\overline{\varepsilon}_{\mathrm{F},t} = N_t^{-1}\sum_i \varepsilon_{\mathrm{F},it}$ is the average of the true idiosyncratic shocks. Pairwise comovements of idiosyncratic shocks lead to non-negligible differences. Define $\overline{\sigma}^2_{\mathrm{F},t} = N_t^{-1}\sum_i \sigma^2_{\mathrm{F},it}$ as the average of idiosyncratic shock variances. Also, denote the average variance of idiosyncratic shocks by $\overline{\overline{\mathrm{cov}}}_{\mathrm{FF},t} = N_t^{-1}\sum_i \overline{\mathrm{cov}}_{\mathrm{FF},it}$ where $\overline{\mathrm{cov}}_{\mathrm{FF},it} =$

[7] See Appendix B for details and other results of simulations with unequal weights.

$(N_t-1)^{-1}\sum_{i'\neq i}\rho_{\mathrm{FF},ii't}\sigma_{\mathrm{F},it}\sigma_{\mathrm{F},i't}$ is the average covariance of firm i with all other firms. Introduction of these terms yields the following lemma.

LEMMA 1: *The difference between the true and pseudo shocks does not converge to zero in mean square when the number of firms goes infinity. For any firm i,*

$$\mathbb{E}\left[|e_{\mathrm{A},t}-\varepsilon_{\mathrm{A},t}|^2\right]=\mathbb{E}\left[|e_{\mathrm{F},it}-\varepsilon_{\mathrm{F},it}|^2\right]=\frac{1}{N_t}\overline{\sigma}^2_{\mathrm{F},t}+\left(1-\frac{1}{N_t}\right)\overline{\overline{\mathrm{cov}}}_{\mathrm{FF},t}. \tag{8}$$

PROOF: From equation (7), $\mathbb{E}\left[|\overline{\varepsilon}_{\mathrm{F},t}|^2\right]=\mathsf{var}(\overline{\varepsilon}_{\mathrm{F},t})$ yields the result. ■

When there are numerous firms, the first term is close to zero with finite variances on the right-hand side of equation (8). However, the second term is not negligible when pairwise covariances are not zero on average. Thus, the squared difference does not converge to zero in mean square. The sample mean and the deviations from it would be undesirable measurements in business cycle research.

3.3. Inconsistent Estimator of Variance and Covariance

From the above result, it is not surprising that variance and covariance of pseudo shocks are an inconsistent estimator of variance and covariance of true shocks in an economy with the non-negligible comovments, $\overline{\overline{\mathrm{cov}}}_{\mathrm{FF},t}\neq 0$. First, the pseudo common and idiosyncratic shocks' variance systemically mis-measures that of the true common and idiosyncratic shocks. Respectively, these values are

$$\mathsf{var}(e_{\mathrm{A},t})=\sigma^2_{\mathrm{A},t}+\frac{1}{N_t}\overline{\sigma}^2_{\mathrm{F},t}+\left(1-\frac{1}{N_t}\right)\overline{\overline{\mathrm{cov}}}_{\mathrm{FF},t}, \tag{9}$$

and

$$\begin{aligned}\mathsf{var}(e_{\mathrm{F},it})=&\left(1-\frac{1}{N_t}\right)\left(\sigma^2_{\mathrm{F},it}-\overline{\mathrm{cov}}_{\mathrm{FF},it}\right)\\&-\left[\frac{1}{N_t}\left(\sigma^2_{\mathrm{F},it}-\overline{\sigma}^2_{\mathrm{F},t}\right)+\left(1-\frac{1}{N_t}\right)\left(\overline{\mathrm{cov}}_{\mathrm{FF},it}-\overline{\overline{\mathrm{cov}}}_{\mathrm{FF},t}\right)\right].\end{aligned} \tag{10}$$

When a firm does not correlate with other firms on average, $\overline{\mathrm{cov}}_{\mathrm{FF},it}=0$, the pseudo variables' variances are consistent estimators. However, they tend to overstate the true common shock's volatility and understate the idiosyncratic shocks' volatility when firms' idiosyncratic shocks comove in the same direction.

More importantly, the pseudo variables yield a misunderstanding of comovements by construction. The covariance between the pseudo common shock and firm i's idiosyncratic shock is

$$\mathsf{cov}(e_{\mathrm{F},it}, e_{\mathrm{A},t}) = \frac{1}{N_t}\left(\sigma^2_{\mathrm{F},it} - \overline{\sigma}^2_{\mathrm{F},t}\right) + \left(1 - \frac{1}{N_t}\right)\left(\overline{\mathrm{cov}}_{\mathrm{FF},it} - \overline{\overline{\mathrm{cov}}}_{\mathrm{FF},t}\right), \tag{11}$$

which is zero on average, i.e., $N_t^{-1}\sum_i \mathsf{cov}(e_{\mathrm{F},it}, e_{\mathrm{A},t}) = 0$. The second term, $\overline{\mathrm{cov}}_{\mathrm{FF},it} - \overline{\overline{\mathrm{cov}}}_{\mathrm{FF},t}$, causes an individual firm to have a non-negligible value when covariances differ across firms even if the true common and idiosyncratic shocks are by definition uncorrelated. The pseudo idiosyncratic shocks' covariance between firm i and i' is

$$\begin{aligned}\mathsf{cov}(e_{\mathrm{F},it}, e_{\mathrm{F},i't}) = \rho_{\mathrm{FF},ii't}\sigma_{\mathrm{F},it}\sigma_{\mathrm{F},i't} - \frac{1}{2}\left(1 - \frac{1}{N_t}\right)\left(\overline{\mathrm{cov}}_{\mathrm{FF},it} + \overline{\mathrm{cov}}_{\mathrm{FF},i't}\right)\\ - \frac{1}{2N_t}\left(\sigma^2_{\mathrm{F},it} + \sigma^2_{\mathrm{F},i't}\right) - \frac{1}{2}\mathsf{cov}(e_{\mathrm{F},it} + e_{\mathrm{F},i't}, e_{\mathrm{A},t}).\end{aligned} \tag{12}$$

The cross-sectional average is negligible by construction, whatever the true idiosyncratic shocks' pairwise correlations are. The following proposition states it formally.

PROPOSITION 1: *The cross-sectional average of pairwise covariances of pseudo idiosyncratic shocks (cross-sectionally demeaned fluctuations) is*

$$\frac{1}{N_t}\sum_i \frac{1}{N_t - 1}\sum_{i' \neq i} \mathsf{cov}(e_{\mathrm{F},it}, e_{\mathrm{F},i't}) = \frac{1}{N_t}\left(\overline{\overline{\mathrm{cov}}}_{\mathrm{FF},t} - \overline{\sigma}^2_{\mathrm{F},t}\right), \tag{13}$$

which converges to zero when the number of firms goes to infinity.

PROOF: Combining equation (11) into equation (12) yields equation (13). ■

Such asymptotically zero average covariance of the pseudo idiosyncratic shocks implies that using deviations from a sample mean as micro shocks potentially rule out the impacts of correlated idiosyncratic shocks on aggregate fluctuations, i.e., clustered origins.

3.4. Homogeneous Variance-Covariance

Even though the correlated idiosyncratic shocks are able to generate notable aggregate fluctuations, most existing business cycle studies have implicitly assumed zero or negligible cross-firm correlations. This subsection shows such assumption can be rationalized when true idiosyncratic shocks have identical variance and covariance regardless of their pairwise correlation. However, Section 5 will show that the variance and covariance notably differ across firms in the US. In that case, this subsection's argument breaks down.

Suppose that all firm have the identical variance and covariance of idiosyncratic shcoks, i.e., $\sigma^2_{\mathrm{F},it} = \sigma^2_{\mathrm{F},t}$ and $\rho_{\mathrm{FF},ii't} = \rho_{\mathrm{F},t}$ for all $i \neq i'$. From equations (9) and (10), their variances are

$$\mathsf{var}(e_{\mathrm{A},t}) = \sigma^2_{\mathrm{A},t} + \frac{1}{N_t}\sigma^2_{\mathrm{F},it} + \left(1 - \frac{1}{N_t}\right)\rho_{\mathrm{F},t}\sigma^2_{\mathrm{F},t}, \tag{14}$$

and

$$\mathsf{var}(e_{\mathrm{F},it}) = \left(1 - \frac{1}{N_t}\right)(1 - \rho_{\mathrm{F},t})\sigma^2_{\mathrm{F},t}. \tag{15}$$

Equations (14) and (15) show that the pseudo variables tend to overstate the true common shock's volatility and understate the idiosyncratic shocks' volatility when the actual pairwise correlation is positive. Despite the above systemic over-and under-measurement problem, the pseudo common and idiosyncratic shocks are still useful in investigating aggregate fluctuations. First, the pseudo common and idiosyncratic shocks are uncorrelated. This zero correlation implies the pseudo variables are well-defined macro and micro shocks. Second, the cross-firm correlation of pseudo idiosyncratic shocks does not depend on the true idiosyncratic shocks and is close to zero where there are many firms. This property allows us to ignore comovements of idiosyncratic shocks.

From equations (11) and (12), firm i's pseudo idiosyncratic shocks are uncorrelated with that of another firm and the pseudo common shock. For $\forall i \neq i'$, I obtain the following results.[8]

$$\mathsf{corr}(e_{\mathrm{F},it}, e_{\mathrm{A},t}) = 0, \tag{16}$$

and

$$\mathsf{corr}(e_{\mathrm{F},it}, e_{\mathrm{F},i't}) = -(N_t - 1)^{-1}. \tag{17}$$

Equation (16) implies that the pseudo shocks $(e_{\mathrm{F},it}, e_{\mathrm{A},t})$ are well defined macro and micro shocks. The newly defined common and idiosyncratic shocks (the sample mean and deviations from the mean) are asymptotically uncorrelated with each other as shown in equation (17). Regardless of pairwise correlations of actual idiosyncratic shocks, the newly-defined idiosyncratic shocks (i.e., firms' demeaned fluctuations) are asymptotically uncorrelated across firms, which implies their negligible contributions to aggregate volatility.

In this homogeneous variance-covariance case, the aggregate fluctuations can be explained by the direct contribution of pseudo common shocks and the conventional granular origins of pseudo idiosyncratic shocks when there are many firms. The conventional decomposition of aggregate volatility into the macro and granular origins without clustered origins works. Using equations (4), (14) and (15), the aggregate volatility is

$$\sigma^2_{\hat{Y},t} = \mathsf{var}(e_{\mathrm{A},t}) + h_t^2 \mathsf{var}(e_{\mathrm{F},it}) - \frac{1 - h_t^2}{N_t - 1} \mathsf{var}(e_{\mathrm{F},it}), \tag{18}$$

where the variance of aggregate fluctuations can be decomposed into the pseudo common and idiosyncratic shocks' variances asymptotically. Therefore, when variance-covariance of true idiosyncratic shocks is identical across firms, business cycle studies do not need to worry about comovements of idiosyncratic shocks across firms by using the pseudo common and idiosyncratic shocks constructed from the observed sample mean and deviation.

[8] Note that the results in equations (16) and (17) hold when the pseudo factors are constructed from the unweighted mean. If the weights are unequal, i.e., consider weighted mean, then the pseudo common and idiosyncratic shocks are correlated, while the pairwise correlation of pseudo idiosyncratic shocks is independent of the true idiosyncratic shocks' pairwise correlation. See Appendix A for the related results with the weighted mean.

In contrast to the previous assumption, a wide range of literature has documented evidence that casts doubt on identical variance or/and covariance of idiosyncratic productivity, output, and financial performance (e.g., Stanley, Amaral, Buldyrev, Havlin, Leschhorn, Maass, Salinger and Stanley, 1996, Xu and Malkiel, 2003, Comin and Philippon, 2005, Comin and Mulani, 2006, Chun, Kim, Morck and Yeung, 2008, Castro, Clementi and Lee, 2015, Tweedle, 2018, Kalnina and Tewou, 2020). Consistent with this, section 5 shows that the US individual firms' business cycle fluctuations and idiosyncratic parts have significant cross-firm variations of their properties including variance and covariance, even within a narrowly defined industry.

Under heterogeneous variance and covariance structure across firms, a cross-sectional sample mean and deviations from it are a poor measure of the common and idiosyncratic parts. Also, pseudo idiosyncratic shocks cannot be justified and used properly. Thus, that environment forces us to recover the true common and idiosyncratic shocks and compute their variance and covariance in order to get a correct investigation of the business cycle and its origins. The next section attempts to identify them to understand aggregate fluctuations' micro origins.

4. Identifying Cluster and Granular Origins of Macro Fluctuations

This paper's primary goal is to quantify the micro origins of aggregate fluctuations. This is complicated by the fact that I observe a firm's business cycle component ($\hat{y}_{it}$), but its true common and idiosyncratic parts ($\varepsilon_{\mathrm{A},t}$ and $\varepsilon_{\mathrm{F},it}$) are nobservable. Without the help of additional information/structure, it is impossible to decompose one component into two parts.

Instead of estimating the point value of true common and idiosyncratic shocks, and their moments, I derive an individual firm's upper and lower bound of the common shock's variance from the variance and covariance of the observed $\{\hat{y}_{it}\}_{i=1}^{N_t}$. Then, I calculate the upper and lower bound of cluster and granular origins by aggregating them within a cluster. This straightforward approach does not require additional assumptions and variables.

Let's begin with observations, $\{\hat{y}_{it}\}_{i=1}^{N_t}$. By definition in equation (1), firms' variance and covariance of business cycle components are as follows.

$$\mathsf{var}(\hat{y}_{it}) = \sigma^2_{\mathrm{A},t} + \sigma^2_{\mathrm{F},it} \tag{19}$$

$$\mathsf{cov}(\hat{y}_{it}, \hat{y}_{i't}) = \sigma^2_{\mathrm{A},t} + \rho_{\mathrm{FF},ii't}\sigma_{\mathrm{F},it}\sigma_{\mathrm{F},i't} \tag{20}$$

Using equations (19) and (20), clustered and granular origins in equation (3) can be rewritten as follows.

$$\chi_t = \sum_i w_{it} \sum_{i' \neq i} w_{i't}\mathsf{cov}(\hat{y}_{it}, \hat{y}_{i't}) - (1 - h_t^2)\sigma^2_{\mathrm{A},t} \tag{21}$$

$$\Gamma_t = \sum_i w_{it}^2 \mathsf{var}(\hat{y}_{it}) - h_t^2 \sigma^2_{\mathrm{A},t} \tag{22}$$

In the above equations, all terms are observable except for $\sigma^2_{\mathrm{A},t}$. The following proposition provides its range.

PROPOSITION 2: *In a cluster, the common shocks' variance should not be larger than* $\sigma^{*2}_{\mathrm{A},t}$.

$$0 \leq \sigma^2_{\mathrm{A},t} \leq \sigma^{*2}_{\mathrm{A},t} = \min_{i,i'} \left\{ \mathsf{var}(\hat{y}_{it}),\ \left[1 + \mathsf{corr}(\hat{y}_{it}, \hat{y}_{i't})\right]\mathsf{sd}(\hat{y}_{it})\mathsf{sd}(\hat{y}_{i't}) \right\} \tag{23}$$

PROOF: First, non-negative variance implies $\mathsf{var}(\hat{y}_{it}) \geq \sigma^2_{\mathrm{A},t}$ in equation (19). Thus, I obtain $\min_i\{\mathsf{var}(\hat{y}_{it})\} \geq \sigma^2_{\mathrm{A},t}$. Second, Cauchy–Schwarz inequality yields $\rho_{\mathrm{FF},ii't}\sigma_{\mathrm{F},it}\sigma_{\mathrm{F},i't} \geq -\sigma_{\mathrm{F},it}\sigma_{\mathrm{F},i't}$. From equation (20), I obtain $\mathsf{cov}(\hat{y}_{it}, \hat{y}_{i't}) + \sigma_{\mathrm{F},it}\sigma_{\mathrm{F},i't} \geq \sigma^2_{\mathrm{A},t}$. Because non-negative $\sigma^2_{\mathrm{A},t}$ implies $\mathsf{var}(\hat{y}_{it}) \geq \sigma^2_{\mathrm{F},it}$ for all i, I obtain that $[1+\mathsf{corr}(\hat{y}_{it}, \hat{y}_{i't})]\mathsf{sd}(\hat{y}_{it})\mathsf{sd}(\hat{y}_{i't}) \geq \sigma^2_{\mathrm{A},t}$ for any i and i'. Thus, $\min_{i,i'}\{[1 + \mathsf{corr}(\hat{y}_{it}, \hat{y}_{i't})]\mathsf{sd}(\hat{y}_{it})\mathsf{sd}(\hat{y}_{i't})\} \geq \sigma^2_{\mathrm{A},t}$. Hence, I obtain equation (23). ■

Using the range of $\sigma^2_{\mathrm{A},t}$, I obtain ranges of clustered and granular origins in equations (21) and (22). A small HHI implies a wide range of clustered origins but a narrow range of granular origins.

COROLLARY 1: *The clustered and granular origins are bounded as follows.*

$$\sum_i w_{it} \sum_{i' \neq i} w_{i't} \mathsf{cov}(\hat{y}_{it}, \hat{y}_{i't}) - (1 - h_t^2)\sigma_{\mathrm{A},t}^{*2} \leq \chi_t \leq \sum_i w_{it} \sum_{i' \neq i} w_{i't} \mathsf{cov}(\hat{y}_{it}, \hat{y}_{i't}) \quad (24)$$

$$\sum_i w_{it} \mathsf{var}(\hat{y}_{it}) - h_t^2 \sigma_{\mathrm{A},t}^{*2} \leq \Gamma_t \leq \sum_i w_{it} \mathsf{var}(\hat{y}_{it}) \quad (25)$$

PROOF: This is directly from Equations (21) and (22) with Proposition 2. ■

The above corollary guides the following section in quantifying clustered and granular origins without any additional assumptions and measurements. Using equations (24) and (25), it is straightforward to calculate the upper and lower bounds of micro origins from data directly.

5. Data and Summary Statistics

I correct the annual firm-level sales and employments data from Compustat North America: Fundamental Annuals during 1975–2018. The measure of productivity is real revenue per worker in logs, on which I use the appropriate industry-level deflators from the US Bureau of Economic Analysis (BEA) database. The data set comprises 53 clusters; disaggregated as much as BEA deflator and Compustat data allow. See Table C.1 for the list of clusters.

Using a panel regression, I compute the business cycle component of firm labor productivity (or real sales) as

$$\hat{y}_{it} = y_{it} - \beta_s y_{it-1} - \psi_s^{\mathrm{age}} \times \ln \mathrm{age}_t - \psi_s^{\mathrm{emp}} \times \ln \mathrm{emp}_t - \psi_s^{\mathrm{time}} \times t - \delta_i, \quad (26)$$

where δ_i is firm fixed effect.[9] As in Castro, Clementi and Lee (2015), the regression equation controls the employment size and age in log because both were shown to be negatively correlated with the dependent variable.[10] The regression allows all coefficients to differ

[9] The firm fixed effect controls the unobserved time-invariant characteristics, including its location and cohort.

[10] See Evans (1987), Hall (1987) for the detailed discussion and empirical evidence in the US manufacturing industries. Models with technology adoption and vintage capital can generate endogenous comovments of aggre-

Table 1. Summary Statistics[a]

Variable		Full sample	1980–1985	1986–2000	2001–2013
Within-firm standard deviation of labor productivity: $\mathsf{var}(\hat{y}_{it})$					
Mean		0.199	0.174	0.205	0.203
Standard deviation		0.226	0.171	0.232	0.238
Quantile	10%	0.058	0.056	0.058	0.059
	50%	0.133	0.126	0.137	0.132
	90%	0.378	0.324	0.396	0.385
Observations (firms)		82,670	13,480	35,750	33,440
Pairwise within-cluster correlation of labor productivity: $\mathsf{corr}(\hat{y}_{it}, \hat{y}_{i't})$					
Mean		0.106	0.086	0.060	0.150
Standard deviation		0.340	0.341	0.328	0.344
Quantile	10%	−0.353	−0.366	−0.380	−0.321
	50%	0.112	0.084	0.064	0.164
	90%	0.559	0.544	0.496	0.602
Observations (pairs)		9,424,466	1,203,324	3,759,910	4,461,232

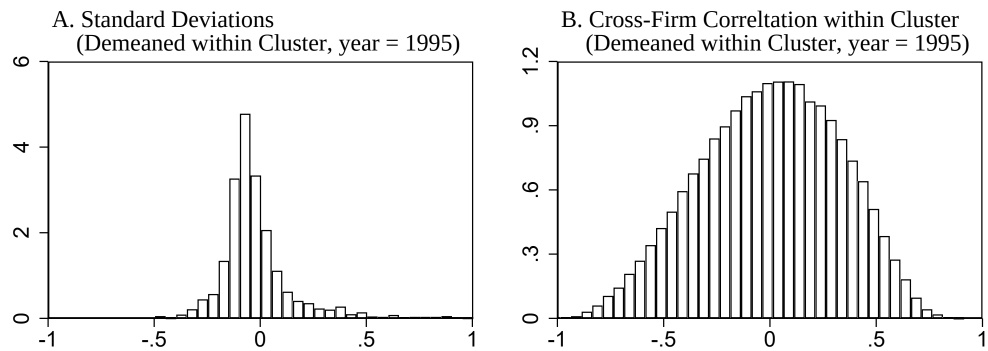
[a] I calculate the firm i's standard deviation and pair of i and i''s correlation at time t with a rolling window of 10 years, $[t-4, t+5]$. The correlations are only for the pairs in the same cluster. There are 53 clusters.

across clusters indexed by s. Lastly, I compute each firm's (time-series) variance and covariance — $\mathsf{var}(\hat{y}_{it})$ and $\mathsf{cov}(\hat{y}_{it}, \hat{y}_{i't})$ — for each year in a rolling window of 10 years, $[t-4, t+5]$. As an alternative, I use the growth rate, $\hat{y}_{it} = y_{it} - y_{it-1}$, instead of the regression residual described in equation (26). The choice of construction of business cycle components does not affect the main results of this paper.

Table 1 presents summary statistics for within-firm volatility and pairwise correlations of labor productivity's business cycle components. Consistent with the results of Comin and Philippon (2005) and Comin and Mulani (2006) with firm sales growths, an individual firm's volatility is larger during the great moderation (1986–2000) compared to earlier periods (1980–1985), even if the macroeconomic fluctuation becomes milder in that era.

gate and firm total factor productivities (e.g., Schaal and Taschereau-Dumouchel, 2018, Mullen, 2020, Fiori and Scoccianti, 2021). The fixed effects, trends, size, and age attempt to control for these endogenous comovments.

Figure 3. Volatility and Cross-Firm Comovements of Labor Productivity's Business Cycle Components



In contrast, the pairwise correlation of labor productivity falls during 1980 and 2000. Recently, the correlation has almost doubled compared to before. Note that these patterns do not represent the evolution of idiosyncratic shock's standard deviation and correlations directly. As shown in equations (19) and (20), they contain the standard deviation of common shocks which I need to recover and isolate to understand the micro origins of aggregate fluctuations.

Related to issues in section 3.4, the rest of this section will provide evidence on the firm heterogeneity of true idiosyncratic shocks' variance and covariance (within a cluster) from the publicly traded US firms' observed firm fluctuations.

To do that, I use firms' variance and covariance of business cycle components, $\mathsf{var}(\hat{y}_{it}) = \sigma^2_{\mathrm{A},t} + \sigma^2_{\mathrm{F},it}$ and $\mathsf{cov}(\hat{y}_{it}, \hat{y}_{i't}) = \sigma^2_{\mathrm{A},t} + \rho_{\mathrm{FF},ii't}\sigma_{\mathrm{F},it}\sigma_{\mathrm{F},i't}$ in equations (19) and (20), respectively. These values should be identical across firms if their variance and covariance of underlying true idiosyncratic shocks are homogeneous. Thus, large cross-sectional variations of $\mathsf{var}(\hat{y}_{it})$ and $\mathsf{cov}(\hat{y}_{it}, \hat{y}_{i't})$ in data cast doubt on the homogeneous variance-covariance assumption for true idiosyncratic shocks.

Figure 3 plots the within-cluster demeaned standard deviations and pairwise correlation coefficients of $\hat{y}_{it}$ in 1995, which examines the hypothesis that firms' true idiosyncratic shocks have identical variance and covariance in their cluster. Panels A and B demonstrate significant heterogeneity. These results are robust over-time and across clusters.

6. The Evolution of Micro Origins in the US

This section presents an account of the evolution of clustered as well as granular origins of the US economy's aggregate GDP volatility in the last three decades. I extend section 4's within-cluster framework to the whole US economy with 53 clusters; dis-aggregated as much as BEA deflator data allow.

To aggregate clusters (industries), I introduce the following variables and notations. An individual firm $i \in I_{st} \subset I_t = \cup_{s' \in S} I_{s't}$ is established in one cluster indexed by $s \in S$. Its shares in the whole economy and in cluster s are w_{it} and w_{sit}, respectively. Also, the share of cluster s in the whole economy is w_{st} satisfying $w_{it} = w_{st} w_{sit}$. Then, the whole economy's business cycle component of GDP is $\widehat{\mathrm{GDP}}_t = d_t \sum_{i \in I_t} w_{it} \hat{y}_{it}$, equivalently, $\widehat{\mathrm{GDP}}_t = d_t \sum_{s \in S} w_{st} \hat{Y}_{st}$ where d_t is the Domar weight adjustment, and $\hat{Y}_{st} = \sum_{i \in I_{st}} w_{sit} \hat{y}_{it}$ is the cluster's (aggregate) business cycle component. The whole economy's volatility is

$$\mathsf{var}(\widehat{\mathrm{GDP}}_t) = d_t^2 \sum_{s \in S} w_{st}^2 \mathsf{var}(\hat{Y}_{st}) + d_t^2 \sum_{s \in S} w_{st} \sum_{s' \in S \setminus \{s\}} w_{s't} \mathsf{cov}(\hat{Y}_{st}, \hat{Y}_{s't}). \tag{27}$$

Equivalently,

$$\mathsf{var}(\widehat{\mathrm{GDP}}_t) = d_t^2 \sum_{s \in S} w_{st}^2 [\sigma_{\mathrm{A},st}^2 + \chi_{st} + \Gamma_{st}] + \mathrm{BIO}_t, \tag{28}$$

where BIO_t is the between-industry origins defined below. The granular and clustered origins of cluster s are $\Gamma_{st} = \sigma_{\mathrm{A},st}^2 + \sum_{i \in I_{st}} w_{sit}^2 \sigma_{\mathrm{F},it}^2$ and $\chi_{st} = \sum_{i \in I_{st}} w_{sit} \sum_{i' \in I_{st} \setminus \{i\}} w_{si't} \rho_{\mathrm{FF},ii't} \sigma_{\mathrm{F},it} \sigma_{\mathrm{F},i't}$. Thus, we can quantify the granular and clustered origins in the whole economy as follows.

DEFINITION 4—Granular origins in the whole economy: $\Gamma_t = d_t^2 \sum_{s \in S} w_{st}^2 \Gamma_{st}$.

DEFINITION 5—Clustered origins in the whole economy: $\chi_t = d_t^2 \sum_{s \in S} w_{st}^2 \chi_{st}$.

The between-industry origins is

$$\mathrm{BIO}_t = d_t^2 \sum_{s \in S} w_{st} \sum_{s' \in S \setminus \{s\}} w_{s't} \left[\mathsf{cov}(\varepsilon_{\mathrm{A},st}, \varepsilon_{\mathrm{A},s't}) + \sum_{i \in I_{st}} w_{sit} \sum_{i' \in I_{s't}} w_{si't} \mathsf{cov}(\varepsilon_{\mathrm{F},it}, \varepsilon_{\mathrm{F},i't}) \right], \tag{29}$$

Figure 4. Clustered and Granular Origins

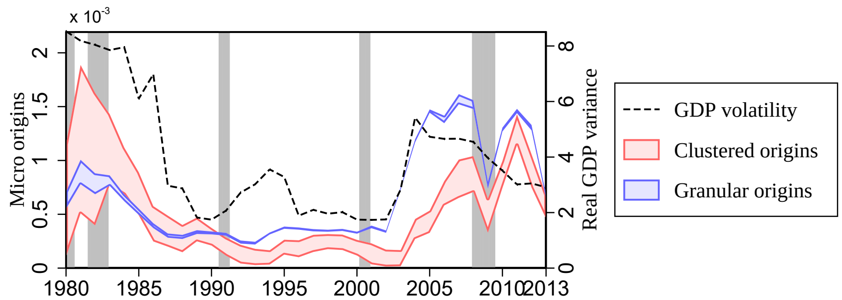
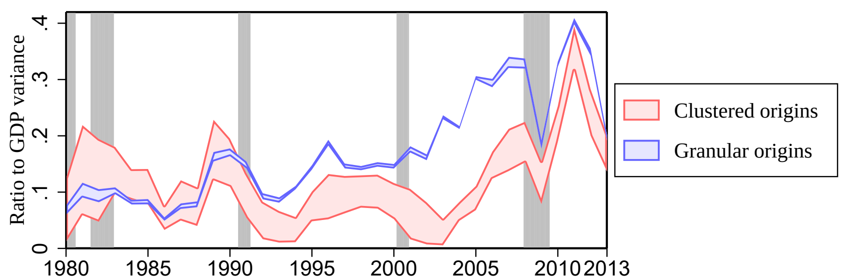


Figure 5. Ratio of Clustered and Granular Origins to GDP Volatility



which contains the correlated sectoral shocks across clusters (the first part in the parenthesis) and the correlated idiosyncratic shocks with firms in other clusters (the second part in the parenthesis). Existing literature has documented the importance of the first term. This paper focuses on the clustered origins: cross-firm correlation within a cluster. I leave issues related to BIO_t open for future research.

Figure 4 plots aggregate GDP volatility and its clustered and granular origins for the US.[11] In the early 1980s, the 10 year rolling window variance of GDP's business cycle components is around 0.7% (8.4% standard deviation). The variance sharply falls to below 0.2% (4.5% standard deviation) during the great moderation era, followed by a rise to 0.4%

[11] Aggregate GDP volatility is calculated as the variance of the US private economy's GDP business cycle components with a rolling window of 10 years, $[t-4, t+5]$, in which the business cycle components are from the residuals of AR(1) similarly to equation (26).

(6.3% standard deviation) after the early 2000s. The figure shows micro origins can well explain the evolution of the US economy's volatility.

Figure 5 plots a ratio of clustered and granular origins to the US economy's GDP volatility. I observe the rise of micro origins of aggregate fluctuations in the US. The red area represents the clustered origins' contribution to the aggregate volatility which is low — around 10% of GDP variance — during the era of great moderation. In the early 2000s, its contribution started rising and is currently around 25% of the US economy volatility now. The blue area — the granular origins' ratio to the GDP variance — steadily increases from 10% to 25% approximately in my sample period.

6.1. Robustness Checks

This subsection discusses issues related to the above results and performs further robustness checks. In Figure 6, the whole economy's Herfindahl-Hirschman Index (HHI) fluctuates over time, but its changes are not drastic so as to generate the time-variations in the micro origins in Figure 4. Also, high HHI is related to clustered origins negatively but granular origins positively. Thus, I conclude that the evolution of HHI is not the primary source deriving the evolution of micro origins.

According to Panel B in Figure 6, Domar adjustment is low in the great moderation era and recently rises. This can generate the observed patterns of micro origins in Figure 4. Figure 7 plots micro origins without Domar adjustments, d_t, from equation (28). The evolution of clustered origins and its relationship with the GDP volatility have the same patterns as Figure 4's results with Domar adjustments. While granular origins recently rise as shown in Figure 4, the 1980s and 1990s have similar granular origins, which differs from Figure 4. A sizable part of granularity's contribution to the great moderation comes from the low Domar weight in that era.

Figure 8 shows that my results are robust to an alternative measure — growth rate — of business cycle components.[12] Also, Figure 9 plots micro origins using business cycle components of the firm's real sales instead of labor productivity. The clustered origins'

[12] In Figure 8, the GDP volatility is also based on its growth rate.

Figure 6. Herfindahl–Hirschman Index and Dormar Adjuestment

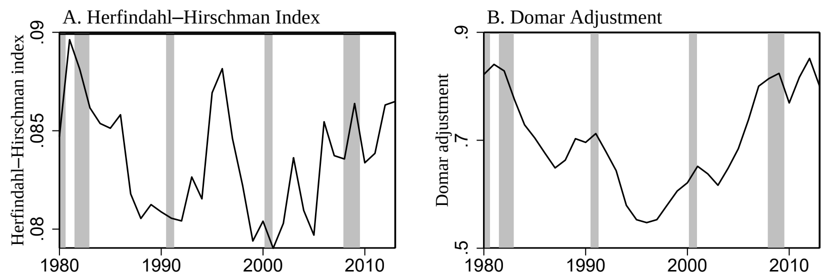


Figure 7. Clustered and Granular Origins without Domar Adjustment

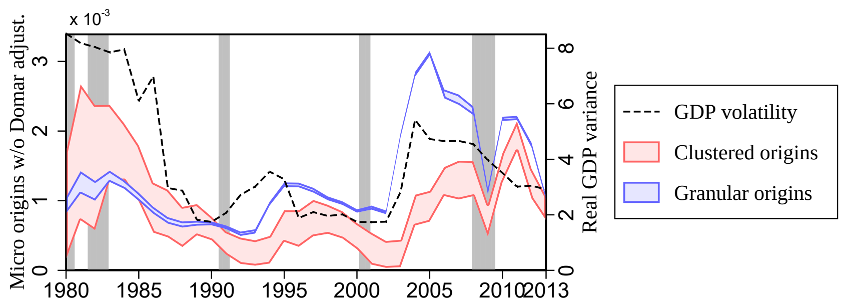


Figure 8. Clustered and Granular Origins with Productivity Growth Rate

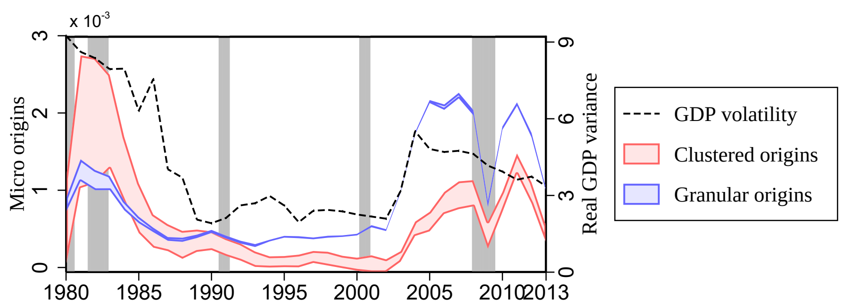
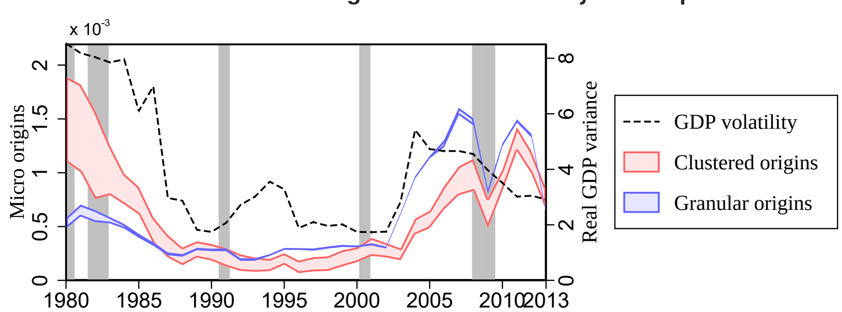


Figure 9. Clustered and Granular Origins with Business Cycle Components of Firm Sales



range is narrower than previously seen in Figure 4 and has a U shape. These results confirm clustered origins are essential to understanding the aggregate economy's business cycle fluctuations.

7. Further Discussion: Factor Model Interpretation

A factor model is an alternative way to handle pairwise correlations in the framework in the previous section. Suppose comovements across idiosyncratic shocks arise from reactions to a latent common factor. Decompose the idiosyncratic shock into the latent factor and (pairwisely) uncorrelated shocks, i.e., $\varepsilon_{\mathrm{F},it} = \lambda_{it} f_t + u_{it}$ where $\varepsilon_{\mathrm{A},t}$, f_t, u_{it} and $u_{i't}$ are uncorrelated for any firm $i \neq i'$. Then, equation (1) can be rewritten by

$$\hat{y}_{it} = \varepsilon_{\mathrm{A},t} + \underbrace{\lambda_{it} f_t + u_{it}}_{=\varepsilon_{\mathrm{F},it}}, \tag{30}$$

which allows a firm's responses to the latent common factor to differ across firms. The business cycle component's variance and covariance are

$$\mathsf{var}(\hat{y}_{it}) = \sigma^2_{\mathrm{A},t} + \mathsf{var}(\lambda_{it} f_t + u_{it}) = \sigma^2_{\mathrm{A},t} + \lambda^2_{it}\sigma^2_{f,t} + \sigma^2_{u,it}, \tag{31}$$

$$\mathsf{cov}(\hat{y}_{it}, \hat{y}_{i't}) = \sigma^2_{\mathrm{A},t} + \mathsf{cov}(\lambda_{it} f_t, \lambda_{i't} f_t) = \sigma^2_{\mathrm{A},t} + \lambda_{it}\lambda_{i't}\sigma^2_{f,t}, \tag{32}$$

where $\lambda^2_{it}\sigma^2_{f,t} + \sigma^2_{u,it}$ and $\lambda_{it}\lambda_{i't}\sigma^2_{f,t}$ are the corresponding part of $\sigma^2_{\mathrm{F},it}$ and $\rho_{\mathrm{FF},ii't}\sigma_{\mathrm{F},it}\sigma_{\mathrm{F},i't}$ in equation (19) and (20) of our benchmark framework.

The latent factor derives pairwise comovements of idiosyncratic shocks. Such comovements prevent the difference between true and pseudo shocks from converging to zero in mean square:

$$\mathbb{E}\left[|e_{\mathrm{A},t} - \varepsilon_{\mathrm{A},t}|^2\right] = \mathbb{E}\left[|e_{\mathrm{F},it} - \varepsilon_{\mathrm{F},it}|^2\right] = \frac{1}{N_t}\overline{\sigma}^2_{u,t} + \overline{\lambda}^2_t\sigma^2_{f,t},, \tag{33}$$

where $\overline{\lambda}_t = N_t^{-1}\sum_i \lambda_{it}$. Compared with the previous benchmark framework, the zero average response, $\overline{\lambda}_t = 0$, means negligible pairwise comovements, $\overline{\mathrm{cov}}_{\mathrm{FF},it} \approx 0$ and thus

$\overline{\overline{\text{cov}}}_{\text{FF},t} \approx 0$, in section 3.[13] The sample mean and deviation from it would not be a good tool in studying business cycle fluctuations and their origins.

Again, the pseudo factor variance (based on a sample mean) is not a consistent estimator.

$$\mathsf{var}(e_{\text{A},t}) = \sigma^2_{\text{A},t} + \overline{\lambda}^2_t \sigma^2_{f,t} + \frac{1}{N_t}\overline{\sigma}^2_{u,t} \tag{36}$$

$$\mathsf{var}(e_{\text{F},it}) = \left(1 - \frac{1}{N_t}\right)\sigma^2_{u,it} + (\lambda_{it} - \overline{\lambda}_t)^2\sigma^2_{f,t} - \frac{1}{N_t}(\sigma^2_{u,it} - \overline{\sigma}^2_{u,t}), \tag{37}$$

where $\overline{\sigma}^2_{u,t} = N_t^{-1}\sum_i \sigma^2_{u,it}$ and $\overline{\lambda}_t = N_t^{-1}\sum_i \lambda_{it}$ are averages. These values are not a good measurement for the true common and idiosyncratic shock variances, $\mathsf{var}(\varepsilon_{\text{A},t})$ and $\mathsf{var}(\varepsilon_{\text{F},it})$, except for negligible comovements case, $\overline{\lambda}_t = 0$. Also, the pseudo common and idiosyncratic shocks' covariances are correlated:

$$\mathsf{cov}(e_{\text{A},t}, e_{\text{F},it}) = (\lambda_{it} - \overline{\lambda}_t)\overline{\lambda}_t\sigma^2_{f,t} + \frac{1}{N_t}(\sigma^2_{u,it} - \overline{\sigma}^2_{u,t}), \tag{38}$$

which converges to zero as the number of firms goes to infinity in the case of $\overline{\lambda}_t = 0$. Also, they are uncorrelated asymptotically when the factor coefficient does not differ across firms, $\lambda_{it} = \overline{\lambda}_t$. In this homogeneous case, the pseudo factors are well-defined macro and micro shocks.[14] However, the identical coefficient implies identical business cycle components' covariance, $\mathsf{cov}(\hat{y}_{it}, \hat{y}_{i't})$ in equation (32), which is inconsistent with data. Finally, the pair-wise covariance of pseudo idiosyncratic shocks tend to ignore the true covariance.

$$\begin{aligned}\mathsf{cov}(e_{\text{F},it}, e_{\text{F},i't}) = (\lambda_{it} - \overline{\lambda}_t)(\lambda_{i't} - \overline{\lambda}_t)\sigma^2_{f,t} - \frac{1}{N_t}\overline{\sigma}^2_{u,t} \\ - \frac{1}{N_t}\left[(\sigma^2_{u,it} - \overline{\sigma}^2_{u,t}) + (\sigma^2_{u,i't} - \overline{\sigma}^2_{u,t})\right]\end{aligned} \tag{39}$$

[13] Note that $\overline{\text{cov}}_{\text{FF},it} = (N_t - 1)^{-1}\sum_{i' \neq i}\mathsf{cov}(\varepsilon_{\text{F},it}, \varepsilon_{\text{F},i't}) = (N_t - 1)^{-1}\sum_{i' \neq i}\mathsf{cov}(\lambda_{it} f_t, \lambda_{i't} f_t)$ implies

$$\overline{\text{cov}}_{\text{FF},it} = \frac{1}{N_t - 1}(-\lambda_{it} + \sum_{i'}\lambda_{i't})\sigma^2_{f,t} = \frac{N_t}{N_t - 1}\left(\overline{\lambda}_t - \frac{\lambda_{it}}{N_t}\right)\lambda_{it}\sigma^2_{f,t} \tag{34}$$

$$\overline{\overline{\text{cov}}}_{\text{FF},t} = \frac{1}{N_t}\sum_i \overline{\text{cov}}_{\text{FF},it} = \frac{N_t}{N_t - 1}\left(\overline{\lambda}^2_t - \frac{1}{N_t^2}\sum_i \lambda^2_{it}\right)\sigma^2_{f,t}. \tag{35}$$

[14] Also, the model of $\hat{y}_{it} = \varepsilon_{\text{A},t} + \varepsilon_{\text{F},it}$ with $\varepsilon_{\text{F},it} = \overline{\lambda}_t f_t + u_{it}$ versus the model of $\hat{y}_{it} = \tilde{\varepsilon}_{\text{A},t} + \tilde{\varepsilon}_{\text{F},it}$ with $\tilde{\varepsilon}_{\text{A},t} = \varepsilon_{\text{A},t} + \overline{\lambda}_t f_t$ and $\tilde{\varepsilon}_{\text{F},it} = u_{it}$ cannot be identified.

Regardless of the value of $\overline{\lambda}_t$, its average is asymptotically zero by construction.

These results show that the previous sections' conclusions hold when pairwise comovements across firms arise from (heterogeneous) responses to a underlying common shock. Also, researchers should carefully consider (1) using a sample mean and deviations as well as (2) implementing zero normalization of average coefficient (as in Bai and Ng, 2013) when the presence of firms' interdependency and networks is expected.

8. Conclusion

Recent business cycle literature has highlighted the importance of individual firms in generating macro fluctuations. However, the fact that correlated idiosyncratic movements across firms within a cluster can generate macroeconomic fluctuations, i.e., clustered origins, has been neglected. This paper distinguishes the micro origins of aggregate fluctuations into clustered and granular origins from the US firm-level data using simple statistical properties. Both the clustered and granular origins account for the US economy's business cycle volatility and its evolution. Specifically, they improve our understanding of the great moderation and the recent macro volatility rise. These results imply that networks and interdependency across firms deserve a central place in business-cycle research, alongside macro and granular origins.

A large part of comovements of individual firms' idiosyncratic labor productivity and sales would come from their endogenous decisions. Recent literature on firm networks in various dimensions (e.g., Oberfield, 2018, Bernard, Moxnes and Saito, 2019, Giroud and Mueller, 2019, Heise, 2019, and many others) can show a question what drives comovements and thus clustered origins. Applying the conventional sectoral level input-output studies (e.g., Long and Plosser, 1983, Bak, Chen, Scheinkman and Woodford, 1993, Horvath, 1998, Dupor, 1999, Foerster, Sarte and Watson, 2011, Atalay, 2017, and many others) on the firm-level also guides us to understand underlying mechanisms. Moreover, vintage capital, technology spillover and adoption (e.g., recently, Bloom, Schankerman and Van Reenen, 2013, Schaal and Taschereau-Dumouchel, 2018, Mullen, 2020, Fiori and Scoccianti, 2021, and many others) can lead to productivity comovements as well.

APPENDIX A: Arbitrary Weights in Section 3.4

Consider an arbitrary weight, $\{\mathrm{w}_{it}\}_i$, satisfying $\sum_{i'} \mathrm{w}_{i't} = 1$ and $\mathrm{w}_{it} \geq 0$. Define pseudo common and idiosyncratic factors based on the weighted mean, as follows.

$$e^{\mathrm{w}}_{\mathrm{A},t} = \sum_{i'} \mathrm{w}_{i't}\hat{y}_{i't} = \varepsilon_{\mathrm{A},t} + \sum_{i'} \mathrm{w}_{i't}\varepsilon_{\mathrm{F},i't} \tag{40}$$

$$e^{\mathrm{w}}_{\mathrm{F},it} = \hat{y}_{it} - e_{\mathrm{A},t} = \varepsilon_{\mathrm{F},it} - \textstyle\sum_{i'} \mathrm{w}_{i't}\varepsilon_{\mathrm{F},i't} \tag{41}$$

Then, the variance of pseudo idiosyncratic shocks is

$$\mathsf{var}(e^{\mathrm{w}}_{\mathrm{F},it}) = (1 - 2\mathrm{w}_{it} + \mathrm{m}^{\mathrm{w}}_2)(1 - \rho_{\mathrm{F},t})\sigma^2_{\mathrm{F},t} \tag{42}$$

where $\mathrm{m}^{\mathrm{w}}_2 = \sum_{i'} \mathrm{w}^2_{i't} \in [N_t^{-1}, 1]$ measures how much equally weighted. Also, the pairwise correlation of pseudo idiosyncratic shocks are

$$\mathsf{corr}(e_{\mathrm{F},it}, e_{\mathrm{F},i't}) = -\frac{\mathrm{w}_{it} + \mathrm{w}_{i't} - \mathrm{m}^{\mathrm{w}}_2}{\sqrt{1 - 2\mathrm{w}_{it} + \mathrm{m}^{\mathrm{w}}_2}\sqrt{1 - 2\mathrm{w}_{i't} + \mathrm{m}^{\mathrm{w}}_2}}, \tag{43}$$

which is independent of the pairwise correlation of true idiosyncratic shocks denoted by $\rho_{\mathrm{F},t}$. If the weights are unequal, the idiosyncratic shocks correlate with the pseudo common in contrast to the equal wights case with homogeneous variance and covariance.

$$\mathsf{corr}(e_{\mathrm{A},t}, e_{\mathrm{F},it}) = -\frac{\mathrm{w}_{it} - \mathrm{m}^{\mathrm{w}}_2}{\sqrt{\dfrac{\sigma^2_{\mathrm{A},t}/\sigma^2_{\mathrm{F},t} + \rho_{\mathrm{F},t}}{1 - \rho_{\mathrm{F},t}} + \mathrm{m}^{\mathrm{w}}_2}\sqrt{1 - 2\mathrm{w}_{it} + \mathrm{m}^{\mathrm{w}}_2}}, \tag{44}$$

where the equal weights — $\forall i$, $\mathrm{w}_{it} = N_t^{-1}$ — lead the pseudo common and idiosyncratic shocks to be uncorrelated for all firms; $\forall i$, $\mathsf{corr}(e_{\mathrm{A},t}, e_{\mathrm{F},it}) = 0$.

APPENDIX B: Simulation Exercise

First, I generate 5,000 firms' true idiosyncratic shocks ($\varepsilon_{\mathrm{F},it}$) during 50 periods which are randomly generated from a multi-normal distribution with mean zero, 12% standard deviation, and 2.5% correlation. Figure B.1 reports results with a time-invariant size distribution with fat-tails where the distribution is generated from Pareto distribution with shape parameter 1.2 on support $[1, \infty)$, which yields approximately a 13% Herfindahl-Hirschman index. Compared to Figure 1, Figure B.1 shows larger aggregate fluctuations due to granularity. Correlations still generate additional aggregate fluctuations. The solid orange line of Panel B with correlations is more volatile than Panel A's solid orange line without correlations. However, the dashed blue lines constructed by pseudo shocks have indistinguishable volatilities between Panels A and B. Second, I redo the above exercise 3,000 times and calculate the sample statistics of true and pseudo idiosyncratic shocks. Figure B.2 plots histograms for the aggregate volatility with and without unequal size distributions. Positive correlations lead to sizable aggregate fluctuations.

Figure B.1. True vs Pseudo Idiosyncratic Shocks and Their Aggregate Fluctuations with fat tails

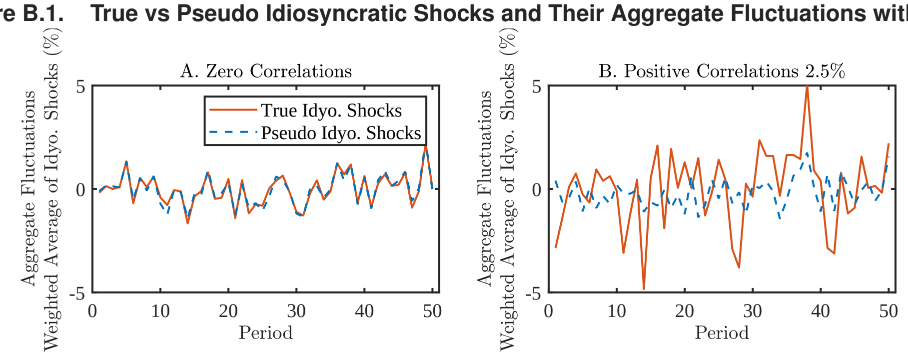
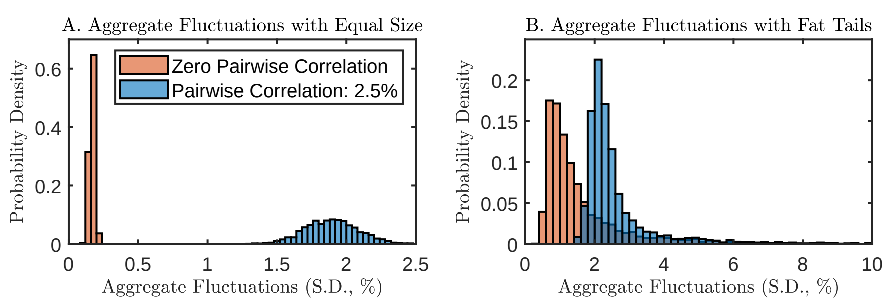


Figure B.2. Sample Standard Deviations of Aggregate Fluctuations



APPENDIX C: Data and Measurements

[Step 1] I correct the industry-level deflators ($\texttt{p}_{st}$) — Chain-Type Price Indexes for Gross Output by Industry [2012=100] — from the US Bureau of Economic Analysis (BEA) database. Sales ($\texttt{sale}_{it}$) and employments ($\texttt{emp}_{it}$) are directly from the Compustat North America: Fundamental Annuals (1975–2018) databases.

[Step 2] I construct the sample as follows. First, I keep the following observations in the Compustat database.

- No major mergers flag: Comparability status ($\texttt{compst}_{it}$) does not equal to AB.
- Country ISO 3 digit code ($\texttt{loc}_{it}$): USA
- Currency ISO 3 digit code ($\texttt{curcd}_{it}$): USD

Then, I exclude firms with the following criteria.

- Non-positive sales
- Non-positive employments
- Utilities sector (NAICS 22)
- Public administration sector (NAICS 91–92)

[Step 3] I merge the Compustat sample and the industry-level BEA deflator using Table C.1. I calculate the logged labor productivity as real sales divided by employments ($\ln \texttt{sale}_{it} - \ln \texttt{p}_{st} - \ln \texttt{emp}_{it}$) for firm i in industry s at t.

[Step 4] Since some clusters have low observations, I merge them. See Table C.1 for the list of clusters.

Table C.1. List of Clusters

Cluster	BEA Industry	NAICS	
		1997	2017
1. Agriculture, forestry, fishing, and hunting	· Farms	111–2	111–2
	· Forestry, fishing, and related activities	113–5	113–5
2. Oil and gas extraction	· Oil and gas extraction	211	211
3. Mining, except oil and gas	· Mining, except oil and gas	212	212
4. Support activities for mining	· Support activities for mining	213	213
5. Construction	· Construction	230	230
6. Wood products	· Wood products	321	321
7. Nonmetallic mineral products	· Nonmetallic mineral products	327	327
8. Primary metals	· Primary metals	331	331
9. Fabricated metal products	· Fabricated metal products	332	332
10. Machinery	· Machinery	333	333
11. Computer and electronic products	· Computer and electronic products	334	334
12. Electrical equipment, appliances, and components	· Electrical equipment, appliances, and components	335	335
13. Motor vehicles, bodies and trailers, and parts, and Other transportation	· Motor vehicles, bodies and trailers, and parts	3361–6	3361–6
Other transportation equipment	· equipment	3369	3369
14. Furniture and related products	Furniture and related products	337	337
15. Miscellaneous manufacturing	Miscellaneous manufacturing	339	339
16. Food and beverage and tobacco products	· Food and beverage and tobacco products	311–2	311–2
17. Textile mills and textile product mills	· Textile mills and textile product mills	313–4	313–4

Continued on next page

Table C.1 — continued from previous page

Cluster	BEA Industry	NAICS 1997	NAICS 2017
18. Apparel and leather and allied products	· Apparel and leather and allied products	315–6	315–6
19. Paper products	· Paper products	322	322
20. Printing and related support activities	· Printing and related support activities	323	323
21. Petroleum and coal products	· Petroleum and coal products	324	324
22. Chemical products	· Chemical products	325	325
23. Plastics and rubber products	· Plastics and rubber products	326	326
24. Wholesale trade	· Wholesale trade	420	420
25. Retail trade	· Motor vehicle and parts dealers	441	441
	· Food and beverage stores	445	445
	· General merchandise stores	452	452
	· Other retail	442-4, 446-8, 451, 453-4	442-4, 446-8, 451, 453-4
26. Air transportation	· Air transportation	481	481
27. Rail transportation	· Rail transportation	482	482
28. Water transportation	· Water transportation	483	483
29. Truck transportation	· Truck transportation	484	484
30. Pipeline transportation	· Pipeline transportation	486	486
31. Other transportation (transit and ground) and support activities, and Warehousing and storage	· Transit and ground passenger transportation	485	485
	· Other transportation and support activities	487-8, 491-2	487-8, 491-2
	· Warehousing and storage	493	493

Continued on next page

Table C.1 — continued from previous page

Cluster	BEA Industry	NAICS	
		1997	2017
32. Publishing industries, except internet (includes software)	· Publishing industries, except internet (includes software)	511	511
33. Motion picture and sound recording industries	· Motion picture and sound recording industries	512	512
34. Broadcasting and telecommunications	· Broadcasting and telecommunications	513	515, 517
35. Data processing, internet publishing, and other information services	Data processing, internet publishing, and other information services	514	518–9
36. Federal Reserve banks, credit intermediation, and related activities	· Federal Reserve banks, credit intermediation, and related activities	521–2	521–2
37. Securities, commodity contracts, and investments	· Securities, commodity contracts, and investments	523	523
38. Insurance carriers and related activities	· Insurance carriers and related activities	524	524
39. Funds, trusts, and other financial vehicles	· Funds, trusts, and other financial vehicles	525	525
40. Real estate	· Real estate	531	531
41. Rental and leasing services and lessors of intangible assets	· Rental and leasing services and lessors of intangible assets	532–3	532–3
42. Computer systems design and related services	· Computer systems design and related services	5415	5415
43. Legal services, and miscellaneous professional, scientific, and technical services	· Legal services	5411	5411
	· Miscellaneous professional, scientific, and technical services	5412–4, 5416–9	5412–4, 5416–9

Continued on next page

Table C.1 — continued from previous page

Cluster	BEA Industry	NAICS	
		1997	2017
44. Administrative and support services	· Administrative and support services	561	561
45. Waste management and remediation services	· Waste management and remediation services	562	562
46. Educational services	· Educational services	610	610
47. Ambulatory health care services	· Ambulatory health care services	621	621
48. Hospitals, Nursing and residential care facilities, and social assistance	· Hospitals	622	622
	· Nursing and residential care facilities	623	623
	· Social assistance	624	624
49. Performing arts, spectator sports, museums, and related activities	· Performing arts, spectator sports, museums, and related activities	711–2	711–2
50. Amusements, gambling, and recreation industries	· Amusements, gambling, and recreation industries	713	713
51. Accommodation	· Accommodation	721	721
52. Food services and drinking places	· Food services and drinking places	722	722
53. Other services, except government	· Other services, except government	810	810

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