A Fallacy of Composition

By Ricardo J. Caballero[*]

The representative-agent framework has endowed macroeconomists with powerful microeconomic tools. Unfortunately, it has also blurred the distinction between statements that are valid at the individual level and those that apply to the aggregate. In this paper I argue that probability theory puts strong restrictions on the joint behavior of a large number of units that are less than fully synchronized. Many fallacies arise from disregarding these restrictions. For example, asymmetric factor adjustment costs at the firm level need not imply asymmetric responses of aggregate employment flows to positive and negative shocks. (JEL E00)

"Fallacy of composition: A fallacy in which what is true of a part is, on that account alone, alleged to be also true on the whole."

[Paul A. Samuelson, 1955]

The representative-agent framework is one of the most important tools for macroeconomists. It allows the use of sophisticated optimization arguments to explain aggregate data. At the same time, microeconomic arguments are typically "intuitive" and therefore convenient conceptualizing devices.

Of course, researchers have never pretended that all agents are literally the same in every dimension, but only that idiosyncrasies have minor impact on the aggregate.[1] This argument is valid on some occasions; however, it is not universally true. In some important cases, idiosyncrasies not only do not wash away but also undo the basic microeconomic feature used to provide the macroeconomic argument. An example of this is due to Andrew S. Caplin and Daniel F. Spulber (1987), where menu-cost pricing

at the firm level is consistent with aggregate price flexibility.

In this paper I attempt to isolate the mechanism underlying the source of several *fallacies of composition*. I argue that the essence of these fallacies relies on the fact that direct microeconomic arguments do not consider the strong restrictions that probability theory puts on the joint behavior of many units that are less than fully synchronized. The microeconomic problem itself often constrains the *endogenous* evolution of the cross-sectional distribution of individual units. In many cases these constraints rule out direct microeconomic explanations of aggregate phenomena.

Examples of these fallacies are plentiful, both in the literature and in everyday discussions. For example, the observation that the aggregate price level is more rigid to downward changes than to upward changes has led many authors to suggest asymmetries at the firm level as responsible for the alleged macroeconomic fact.[2] The basic insight developed in this paper shows that asymmetric policies at the firm level do not necessarily imply asymmetries in upward and downward adjustments of the aggregate price level. Similarly, asymmetric factor adjustment costs at the firm level need not

[1] An important exception is the imperfect-information framework, as in Robert E. Lucas (1973).

[2] For a description of aggregate price-level asymmetries, see Phillip D. Cagan (1979); for an attempt to use direct microeconomic arguments to account for such asymmetry, see Timur Kuran (1983).

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imply asymmetric responses of the aggregate capital stock and the level of employment to positive and negative shocks.

These issues have derived new prominence from the recent finding by Steven J. Davis and John Haltiwanger (1989) and Olivier J. Blanchard and Peter A. Diamond (1989) (the DH/BD fact, hereafter) that the cyclic behavior of gross job reallocation in the United States is driven by job destruction as opposed to job creation. Since the natural tendency is to propose microeconomic asymmetries (e.g., bankruptcy, asymmetric adjustment costs, etc.) as explanations for this, I use the DH/BD framework to illustrate the main point of the paper. I show that direct arguments based on microeconomic job creation and destruction asymmetries do not necessarily imply aggregate flow asymmetries. Of course the arguments used for this case extend to the aggregate price-level asymmetry and capital-stock examples mentioned above, as well as many others.

Although the main motive of the paper is to describe and explain the fallacies of composition described above, I depart briefly and discuss a mechanism to generate aggregate asymmetries in heterogeneous-agent models. This mechanism is based on the presence of events that violently reshape the cross-sectional distribution; sharp recessions and oil shocks are good examples of such events. Interestingly, this *sample-path* source of asymmetry does not depend on the presence or absence of microeconomic asymmetries.[3]

The remainder of the paper is organized in five sections (and an appendix). Section I introduces the basic microeconomic model and the corresponding limit-probability arguments. Sections II and III discuss long-run and dynamic behavior of aggregate flows. Section IV describes a mechanism to generate aggregate asymmetries, and conclusions are presented in Section V.

I. Microeconomic Behavior

Since my objective is to study the aggregate impact of *given* microeconomic policy rules, I limit the discussion in this section to a description of a set of *given* behavioral rules for microeconomic units. I discuss the impact of relaxing these rules in the conclusion.[4]

Let each individual firm i have a desired (frictionless) level of employment at time t, equal to L_{it}^*. Due to some friction (e.g., hiring and firing costs), actual employment at the firm level (L_{it}) is not always equal to the frictionless optimal level; the difference between L_{it} and L_{it}^* is denoted by D_{it}. Suppose now that firms have a threshold rule—as is true in the presence of nonconvexities in the adjustment technology—so that they fire workers (destroy jobs) when D_{it} crosses an upper threshold T and hire (create jobs) when D_{it} crosses a lower threshold B. The quit rate is zero, so actual employment is constant at all other instances.

The firm's frictionless level of employment is driven by a standard binomial random walk:

$$
L_{it}^* = L_{it-1}^* + \begin{cases} +1 & \text{with probability } \tfrac{1}{2} \\ & \text{(good shock)} \\ \\ -1 & \text{with probability } \tfrac{1}{2} \\ & \text{(bad shock)}. \end{cases}
$$

The microeconomic asymmetry takes the following simple form: during a job-creation period the firm hires fewer workers than it dismisses during a job-destruction period (as happens, for example, when larger fixed costs are involved in job destruction than in job creation). Let H and F be the number of workers hired and fired during times of job creation and job destruction, respectively. To fix ideas, I will start with a very

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[3]This does not mean that the latter are not present. However, see Dennis W. Carlton (1986) for evidence on the absence of price asymmetry at the firm level.

[4]See, for example, Giuseppe Bertola and Caballero (1990) for a justification of the microeconomic rules adopted here and a discussion of the dependence of these rules on deep parameters.

simple case in which $T = 1$, $B = -1$, $H = 1$, and $F = 2$.

Here D_{it} can take only three values: -1, 0, and 1. When D_{it} is at -1, there is a probability equal to $\frac{1}{2}$ that desired employment will increase further, leading the firm to hire another worker, which means that D_{it+1} remains at -1 ($D_{it+1} = -1 - 1 + 1$). There is also a probability equal to $\frac{1}{2}$ that desired employment falls, in which case $D_{it+1} = 0$. When $D_{it} = 0$, there is neither hiring nor firing at $t + 1$, and D_{it+1} can be either at -1 or 1 with equal probability. Finally, when $D_{it} = 1$ there is a probability equal to $\frac{1}{2}$ that in the next period the firm will destroy two jobs, and a probability equal to $\frac{1}{2}$ that desired employment rises; thus $D_{it+1} = 0$ with probability 1. All these statements can be summarized in a simple transition matrix, $\mathbf{P}$:

$$\mathbf{P} = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 1 & 0 \end{bmatrix}$$

where the rows represent the position of D_{it} and the columns that of D_{it+1}. For example, position (3,2) in this matrix indicates that starting from $D_{it} = 1$, $D_{it+1} = 0$ with probability 1.

Let $p_t(-1)$, $p_t(0)$, and $p_t(1)$ be the probabilities of D_t being at -1, 0, and 1, respectively. For now I concentrate on the characteristics of the limiting probability (row) vector, denoted by $\mathbf{p}$.[5]

By definition, each stationary probability $p(h)$ must be equal to the sum of the probabilities $p(k)$ weighted by the probabilities of moving from each state k to state h. In matrix form:

$$\mathbf{p} = \mathbf{p}\mathbf{P}$$

or, equivalently,

(1) $p(0) = \frac{1}{2}p(-1) + p(1)$

(2) $p(-1) = \frac{1}{2}p(0) + \frac{1}{2}p(-1)$

(3) $p(1) = \frac{1}{2}p(0)$

and the adding-up condition must be satisfied:

$$p(-1) + p(0) + p(1) = 1.$$

Stationary probabilities can be interpreted as the relative time spent in each state. A direct consequence of this is that job creation will occur with frequency $\frac{1}{2}p(-1)$ and job destruction with frequency $\frac{1}{2}p(1)$. However, replacing (3) in (2) yields

$$p(1) = \frac{1}{2}p(-1)$$

which means that the counterpart of the asymmetry in the size of hiring and firing is that job creation occurs twice as often as job destruction. Figure 1A provides an example of this by showing a randomly picked sample path of job creation and destruction by a firm behaving according to the rules described in this section, while Figure 1B shows $\mathbf{p}$.

The simple observation that there is a negative relation between size and frequency of adjustment is at the root of the results obtained for the aggregate level in the next sections. There, probability statements for individual firms become cross-sectional statements.

II. Stationarity and Flows

The main concern of this paper is not the probability distribution of individual firms, but the characteristics of aggregate sample paths. The reason for the previous section is that many probability statements at the individual level can be used to describe the path of the realized cross-sectional distribution of the D_{it}'s, which is sufficient to describe the behavior of aggregate flows.

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[5] It is immediate to show that this Markov chain is ergodic (i.e., starting from any vector of probabilities $\mathbf{p}_0$, eventually the time index becomes irrelevant).
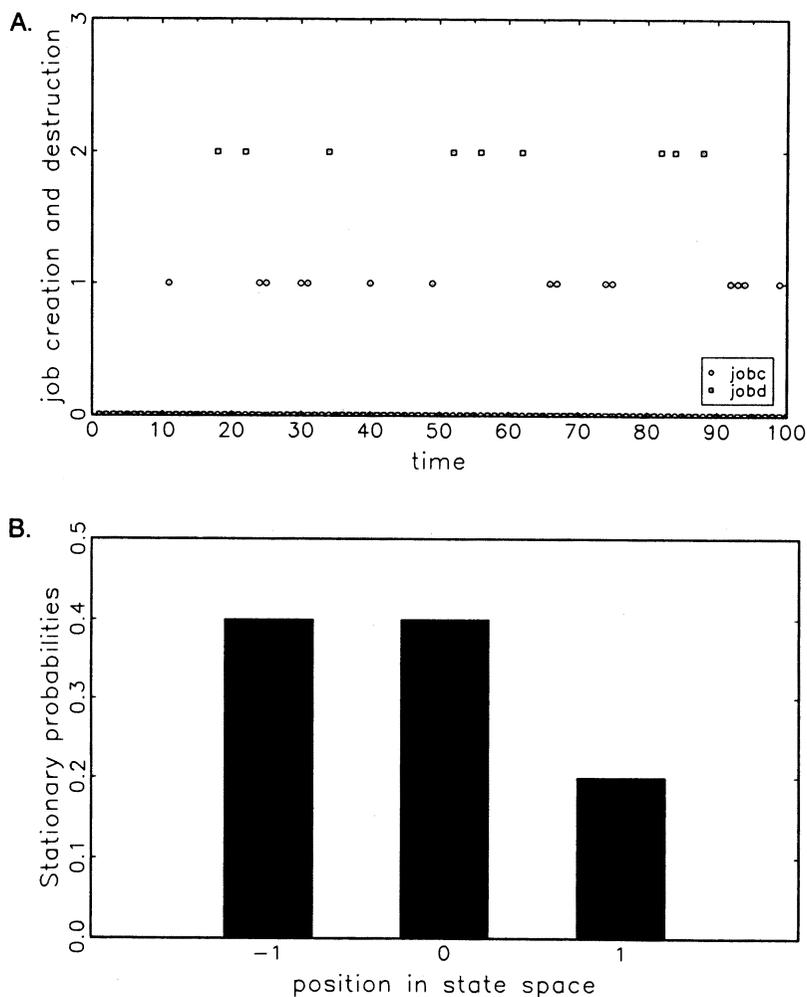
FIGURE 1. A) JOB CREATION AND JOB DESTRUCTION BY AN INDIVIDUAL FIRM;
B) STATIONARY PROBABILITIES/OCCUPANCY FREQUENCIES

Notes: Circles (jobc) and squares (jobd) denote job creation and job destruction, respectively. The sample path of aggregate shocks used in panel A was randomly generated by a standard binomial random walk. The initial D_i was set equal to zero but the figure starts after 200 shocks have already occurred.

There is of course one case in which the description of the *path* of an individual firm is sufficient to describe the path of the aggregate. This is the frequently used representative-agent model, which corresponds to a situation in which firms not only have the same policy rules but also start from the same position (i.e., $D_{i0} = D_0$ for all i) and are affected by the same shocks. As said before, here all the statements for the individual firm are valid for the aggregate. Most importantly, job destruction occurs with half the frequency of job creation, but when it occurs it is twice as large as job creation. The strong microeconomic asymmetry remains intact at the aggregate level, validating the microeconomic story of aggregate phenomena.

The degree of synchronization of units' actions in the previous example is far-fetched, however. In what follows, I study the impact of less than perfectly correlated shocks across firms on the (lack of) influence that microeconomic asymmetries have on aggregate outcomes. For this I assume that there is a large number of firms that follow identical hiring and firing rules with their respective L_{it}^* paths described by standard binomial random walks, which I initially assume to be uncorrelated across firms. I leave the more complex case in which shocks are correlated (although not perfectly) across firms for the next section.

The case in which shocks are independent across firms is almost as straightforward as the representative-agent model. Take any probability distribution to describe the possible values of firm i's D_{it} at time t, and let this probability distribution be the same across all firms. Then the realized *cross-sectional* distribution will be "equal" (in the sense that it will converge as the number of firms gets very large) to the common *probability* distribution describing the possible positions of an individual firm. This is a direct application of the Glivenko-Cantelli theorem (see Patrick Billingsley, 1986). It is important because it allows one to interpret statements about probabilities at the firm level as statements about the fraction of firms in different positions of the state space of D_{it}. Combining this interpretation with the ergodicity property of the Markov chain described in the previous section determines that starting from any cross-sectional distribution on the space of the D_{it}'s, eventually the cross-sectional distribution becomes stationary; that is, individual firms change their positions continuously, but the cross-sectional distribution remains unchanged.

The importance of the steady-state result described in the previous paragraph is that job destruction and job creation ultimately become constant. In this state there is a fraction $(\frac{1}{2})p(-1)$ (per period) of firms hiring one worker each, and a fraction $(\frac{1}{2})p(1)$ of firms firing two workers each. However, as $p(1) = (\frac{1}{2})p(-1)$, job creation and destruction are not only constant but equal.

Thus, *in the absence of aggregate fluctuations, the size of the flows in and out of employment has nothing to do with the microeconomic asymmetry*.

Of course, the previous paragraph results trivially from the definition of a steady state and is a statement about the levels of job creation and job destruction, not about their volatility. However, simple as it is, it illustrates the basic mechanism that causes fallacies of composition even outside the steady state: when the departures of firms' state variables from their frictionless counterpart are stationary and there is sufficient heterogeneity across agents, the cross-sectional distribution often counteracts the microeconomic asymmetry.

III. Aggregate Shocks and Flows

The most interesting case for macroeconomists, however, is when there is a nonvanishing (but less than perfect) correlation in the shocks across firms (i.e., when there are *aggregate* shocks). In this case, the probability statements for individual firms still go through, but the relation between these probability statements and the behavior of the cross-sectional distribution is more subtle. In particular, it is no longer true that the realized cross-sectional distribution converges to a stationary state.

At this point it is helpful to highlight the connection and differences between this section and the previous one. First, the Glivenko-Cantelli theorem still applies after conditioning on the entire path of aggregate shocks (which was also true in the previous section, but there the common or aggregate component of shocks was deterministic and constant). Thus, one can still draw analogies between probability statements at the firm level and cross-sectional statements, but now statements are conditional on the realization of aggregate shocks. Second, since the path of aggregate shocks—the conditioning variable—is no longer constant, the cross-sectional distribution generally does not settle down.[6] Third, since it is still true that

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[6] This also throws light on the exceptions to the nonconvergence proposition. These are cases in which

the probability distribution of the position of a firm converges to the distribution described in Section I, where firms spend on average twice as much time near the hiring barrier than near the firing barrier, then it must be the case that the aggregate has on average (over time and sample paths) twice as many individuals near the hiring barrier, offsetting the microeconomic asymmetry on average (over time and sample paths).

The insights of the previous paragraph and Sections I and II help answer the following questions:

(i) How does the presence of idiosyncratic shocks affect the impact that microeconomic asymmetries have on the path of aggregate flows?
(ii) How important are the particular features of the sample path of aggregate shocks in determining the dynamic properties of aggregate flows and the answer to the first question?

The first question is discussed in this section, while the second one is examined in Section IV.

To consider aggregate shocks, I modify the model above by changing the microeconomic probabilities of positive and negative shocks according to the current state of the economy. The L_{it}^*'s are now driven by switching random walks. In good times,

$$L_{it}^* = L_{it-1}^* + \begin{cases} +1 & \text{with probability } \lambda_g \\ & \text{(good shock)} \\ \\ -1 & \text{with probability } 1 - \lambda_g \\ & \text{(bad shock)} \end{cases}$$

conditional and unconditional (on the aggregate path) distributions eventually become the same (i.e., the cross-sectional distribution becomes independent of the aggregate path). A well-known example of a steady-state result of this type is given by Caplin and Spulber (1987): a distribution uniform on the space of a one-sided (S, s) model is unchanged by variations in the path of money as long as this path is monotonic and continuous. Caballero and Eduardo M. R. A. Engel (1991) provides the full-convergence description of this case and shows how independence is achieved over time.

and in bad times

$$L_{it}^* = L_{it-1}^* + \begin{cases} +1 & \text{with probability } \lambda_b \\ & \text{(good shock)} \\ \\ -1 & \text{with probability } 1 - \lambda_b \\ & \text{(bad shock)}. \end{cases}$$

I assume that good and bad times occur with probability $\frac{1}{2}$ each, which yields:[7]

(4) $\lambda_g = \frac{1}{2}(1 + \delta)$

                       $\lambda_b = \frac{1}{2}(1 - \delta)$

where δ is the fraction of the total uncertainty faced by an individual firm that is due to aggregate uncertainty. For example, a value of λ_g of 0.65 corresponds to a δ equal to 30 percent; that is, 30 percent of the total uncertainty faced by individual firms comes from aggregate uncertainty.

In addition to symbolizing the probability of a good shock at the individual level, λ_g represents the fraction of firms that receive a good shock in good times, whereas λ_b is the fraction of firms that receive a good shock during bad times. Good and bad times are then determined by whether more or less than half of the firms are affected by good shocks. In what follows, I reserve the terminology good and bad *times* to describe macroeconomic events, and I use good and bad *shocks* to describe microeconomic events. In the example, this interpretation says that $\lambda_g = 0.65$ means that in good times 65 percent of the firms receive a positive shock, and 35 percent receive a negative one. During bad times these proportions are reversed.[8]

With aggregate uncertainty, the transition matrix varies with the state of the world. In the simple three-states example presented

[7]See the Appendix for the case $q = \frac{1}{2}$.
[8]Note that the continuous time limit of the stochastic process describing the path of each L_i^* converges to the sum of two independent Brownian motions: one for the common shock across firms and another for the idiosyncratic component.

above, and denoting by $\mathbf{P}_g$ and $\mathbf{P}_b$ the values attained by the transition matrix during good and bad times, respectively, one has

$$\mathbf{P}_g = \begin{bmatrix} \lambda_g & 1-\lambda_g & 0 \\ \lambda_g & 0 & 1-\lambda_g \\ 0 & 1 & 0 \end{bmatrix}$$

$$\mathbf{P}_b = \begin{bmatrix} \lambda_b & 1-\lambda_b & 0 \\ \lambda_b & 0 & 1-\lambda_b \\ 0 & 1 & 0 \end{bmatrix}.$$

In what follows I enlarge the state space so that the D_{it}'s now take values between -7 and 7 (i.e., there are 15 positions in the state space), in order to reduce the impact of the state-space discreteness in the numerical examples provided below. The microeconomic asymmetry is made even more pronounced: job creation is still equal to 1, whereas job destruction is now equal to 6. Thus, firms wait until the shortage of workers (with respect to the frictionless optimal) exceeds (in absolute value) -7 to hire *one* worker, returning to the position $D_{it} = -7$; on the other hand, they wait until the excess of labor goes beyond 7 to fire *six* workers, returning to the position $D_{it} = -2$.

Aggregate job-creation and job-destruction flows are equal to $\lambda_t p_t(-7)$ and $6(1-\lambda_t)p_t(7)$, respectively. The issue addressed in this section, then, is whether there is a tendency in $\lambda_t p_t(-7)$ to fluctuate sufficiently more than $(1-\lambda_t)p_t(7)$ to offset the impact of the microeconomic asymmetry on aggregate flows.

A formal and general answer to this question is very difficult; therefore, I illustrate the answer and some of its caveats though several examples based on the simple framework built up to now. Using (4) with $\lambda_g = 0.65$ and the microeconomic parameters described above, I generate 1,000 replications of samples of 200 periods each.[9]

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[9]Strictly speaking, using longer sample sizes brings the simulations closer to their theoretical limits; I have chosen small samples to analyze the results in a context more comparable to that of the actual empirical evidence. Conversely, smaller samples increase the dispersion of the results.

TABLE 1—AGGREGATE FLOWS VOLATILITY

Condition	$\dfrac{\sigma_{\text{jobc}}}{\bar{x}_{\text{jobc}}}$	$\dfrac{\sigma_{\text{jobd}}}{\bar{x}_{\text{jobd}}}$
Microeconomic asymmetry	0.687	0.687
	(0.159)	(0.158)
Microeconomic symmetry	0.691	0.687
	(0.188)	(0.187)

Notes: Both rows are generated with the same seeds. The basic parameters are $\delta = 0.3$, $q = 0.5$, and $\lambda_g = 0.65 = 1 - \lambda_b$. In the column headings, $\bar{x}_{\text{jobc}}$ and $\bar{x}_{\text{jobd}}$ are the averages across all samples of the mean (over time) job creation and job destruction; σ_{jobc} and σ_{jobd} are the averages across samples of the (within-sample) standard deviations of job creation and job destruction. The numbers in parentheses are the standard deviations of σ_{jobc} and σ_{jobd} divided by (the constants) $\bar{x}_{\text{jobc}}$ and $\bar{x}_{\text{jobd}}$.

The first row in Table 1 summarizes the results of this experiment. The columns report the average across samples of the (within-sample) standard deviations of job creation and job destruction, normalized by the average across all samples of the mean (over time) job creation and job destruction.[10] The second row in Table 1, on the other hand, reports the results of the same experiment of the first row but with one important difference: there is no microeconomic asymmetry. As before, firms hire one worker when crossing the lower threshold, but now firms fire *one* worker (instead of six) when crossing the upper threshold.

The table speaks for itself: there is no evidence of systematic aggregate asymmetry in the volatility of job creation and destruction. Moreover, this conclusion is independent of the degree of asymmetry of the microeconomic policy rule.

Figure 2 provides another illustration of the basic message in Table 1. Using the same set of parameters, the figure shows aggregate job-creation and job-destruction flows after consecutive positive and negative aggregate shocks (the number of consecutive shocks is on the x-axis), starting from a

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[10]This statistic is not the average coefficient of variation, since the standard deviations of all samples are normalized by a common, overall mean.
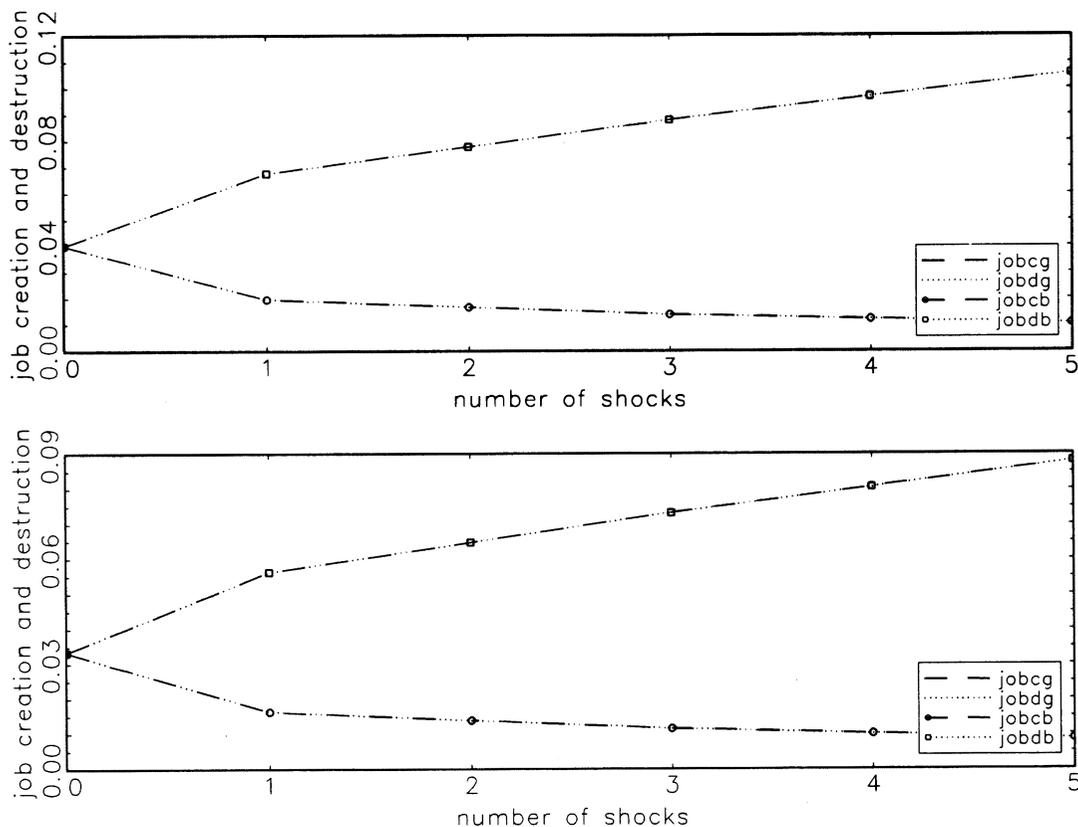
FIGURE 2. JOB CREATION AND DESTRUCTION DURING GOOD AND BAD TIMES: A) ASYMMETRIC
MICROECONOMIC POLICY; B) SYMMETRIC MICROECONOMIC POLICY

Notes: The initial distribution is the ergodic distribution of an individual firm; $\lambda_g = 0.65 = 1 - \lambda_b$. Asymmetric microeconomic policy: job creation and job destruction (when they occur) are equal to 1 and 6, respectively. Symmetric microeconomic policy: job creation and job destruction (when they occur) are equal to 1.

cross-sectional distribution equal to the er-godic distribution of an individual D_i.[11] Figure 2A corresponds to the microeconomic-asymmetry case, while Figure 2B corresponds to the microeconomic-symmetry case. The plain lines depict job creation (dashed) and job destruction (dotted) for a sequence of positive shocks, while the lines with symbols do the same for a sequence of negative shocks. The message is clear: when

[11]Caballero and Engel (1992) shows that this is the "initial distribution" that yields the average (over all possible initial distributions) response of the system to a given sequence of aggregate shocks.

aggregate fluctuations interact with idiosyn-cratic shocks, the steady-state result of the previous section is preserved in a much more subtle way; the offsetting of the microeco-nomic asymmetry through the cross-sec-tional distribution occurs at the mirror-image states of the world (very good booms with very bad recessions, mild booms with mild recessions, etc.). This is reflected in the figure by the superposition of creation and destruction curves for the opposite states of the world.

To summarize, *when heterogeneity is suf-ficiently strong, the cross-sectional distribu-tion tends to undo microeconomic asymme-*
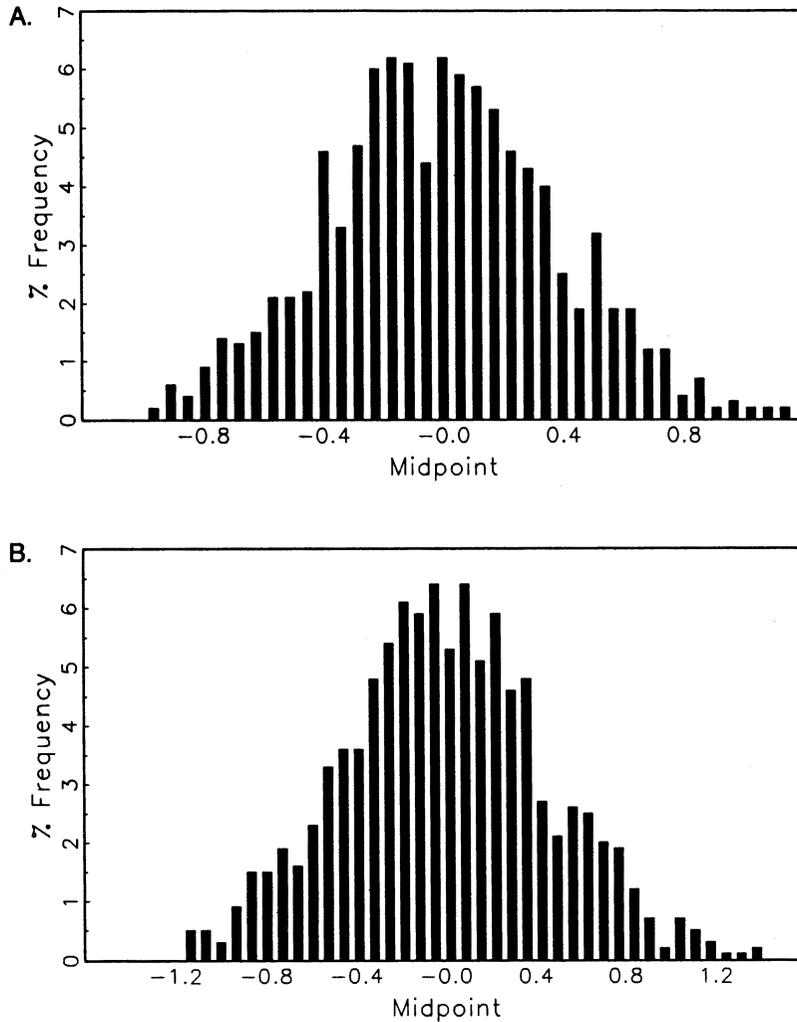
FIGURE 3. HISTOGRAMS OF RELATIVE VOLATILITY OF AGGREGATE JOB
CREATION AND DESTRUCTION: A) ASYMMETRIC MICROECONOMIC POLICY;
B) SYMMETRIC MICROECONOMIC POLICY

Notes: Relative volatility is measured (in each sample) by the statistic $(\sigma_{jobc} - \sigma_{jobd})/\bar{\sigma}$, where $\bar{\sigma} \equiv (\sigma_{jobc} + \sigma_{jobd})/2$. The histograms correspond to 1,000 random replications of samples of 200 observations each, with $\lambda_g = 0.65 = 1 - \lambda_b$.

tries. Disregarding this effect may yield important fallacies of composition.

IV. Generating Aggregate Asymmetries

The final statement of the previous section included the condition that heterogeneity be sufficiently strong. If this is not so, the model cannot depart sufficiently from the simple representative-agent model in which microeconomic asymmetries are directly reflected on aggregate outcomes. More interesting and realistic, however, is to generate aggregate asymmetries within the context of a model in which there is significant heterogeneity across firms. In this section, I provide an example of how to generate these asymmetries.

Figure 3 provides the first clue. The figure contains the histograms of the difference in the standard deviations of job creation and destruction normalized by the average of these two standard deviations. Figure 3A corresponds to row 1 of Table 1, while Figure 3B corresponds to row 2 of Table 1. Both figures show that samples in which the standard deviation of one of the flows is substantially larger than that of the other one are not too rare. The main lesson to extract from these figures is that the particular features of the sample path of the aggregate driving process play a crucial role in shaping the behavior of aggregate flows. Good and bad draws of aggregate realizations shape the cross-sectional distribution of firms, which is a key element for aggregate dynamics,[12] as discussed throughout the paper.

A more dramatic case of asymmetry in aggregate flows is obtained by linking the asymmetry in the aggregate driving process to the degree of coordination of individual firms. To do this I modify the probabilistic model used to generate the previous figures and table. In particular, I make assumptions such that contractions are typically shorter but more severe than expansions.[13]

Two simple modifications deliver the desired features in the driving process, while preserving the average balance between job creation and job destruction:[14] (i) let q, the probability of good times, be larger than 0.5 (see the Appendix), and (ii) let $\lambda_b < 1 - \lambda_g$, so bad times are sharper than good times. In particular, let $q = 0.75$, which means that

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[13] See, for example, Salih N. Neftçi (1984) and Daniel Sichel (1989). Also notice that generating asymmetric flows when the sample path of the driving force is asymmetric is not as straightforward as it may first look. It is direct to show that asymmetries in the aggregate driving process yield asymmetries in the *net* flows series, but there is no a priori reason for the gross creation and destruction flows themselves to be asymmetric.

[14] This avoids adding a drift to employment, which would clutter the comparisons with the previous section.

TABLE 2—ASYMMETRIC AGGREGATE
FLOWS VOLATILITY

Condition	$\dfrac{\sigma_{jobc}}{\bar{x}_{jobc}}$	$\dfrac{\sigma_{jobd}}{\bar{x}_{jobd}}$
Microeconomic asymmetry	0.524	0.672
	(0.149)	(0.297)
Microeconomic symmetry	0.522	0.669
	(0.170)	(0.313)

Notes: Both rows are generated with the same seeds. The basic parameters are $\delta = 0.3$, $q = 0.75$, $\lambda_g = 0.59$, and $\lambda_b = 0.24$. In the column headings, $\bar{x}_{jobc}$ and $\bar{x}_{jobd}$ are the averages across all samples of the mean (over time) job creation and job destruction; σ_{jobc} and σ_{jobd} are the averages across samples of the (within-sample) standard deviations of job creation and job destruction. The numbers in parentheses are the standard deviations of σ_{jobc} and σ_{jobd} divided by (the constants) $\bar{x}_{jobc}$ and $\bar{x}_{jobd}$.

a positive aggregate shock is three times more likely than a negative one. The relation between λ_b and $1 - \lambda_g$ is then determined by the condition that aggregate flows be equal on average, which after a few transformations yields

$$\lambda_b = \frac{1}{2}\left[1 + (1 - 2\lambda_g)\frac{q}{1-q}\right].$$

This implies that equation (4) is replaced by:

$$(5) \qquad \lambda_g = \frac{1}{2}\left(1 + \delta\sqrt{\frac{1-q}{q}}\,\right)$$

$$\lambda_b = \frac{1}{2}\left(1 - \delta\sqrt{\frac{q}{1-q}}\,\right).$$

Except for these modifications, Table 2 and Figures 4 and 5 are the analogues of Table 1 and Figures 3 and 2, respectively. Table 2 is constructed by using (5) with $\delta = 0.3$ and $q = 0.75$, to generate 1,000 replications of samples of 200 periods each. The first row in Table 2 summarizes the results of this experiment for the microeconomic-asymmetry case. The columns report the average across samples of the (within-sample) standard deviations of job creation
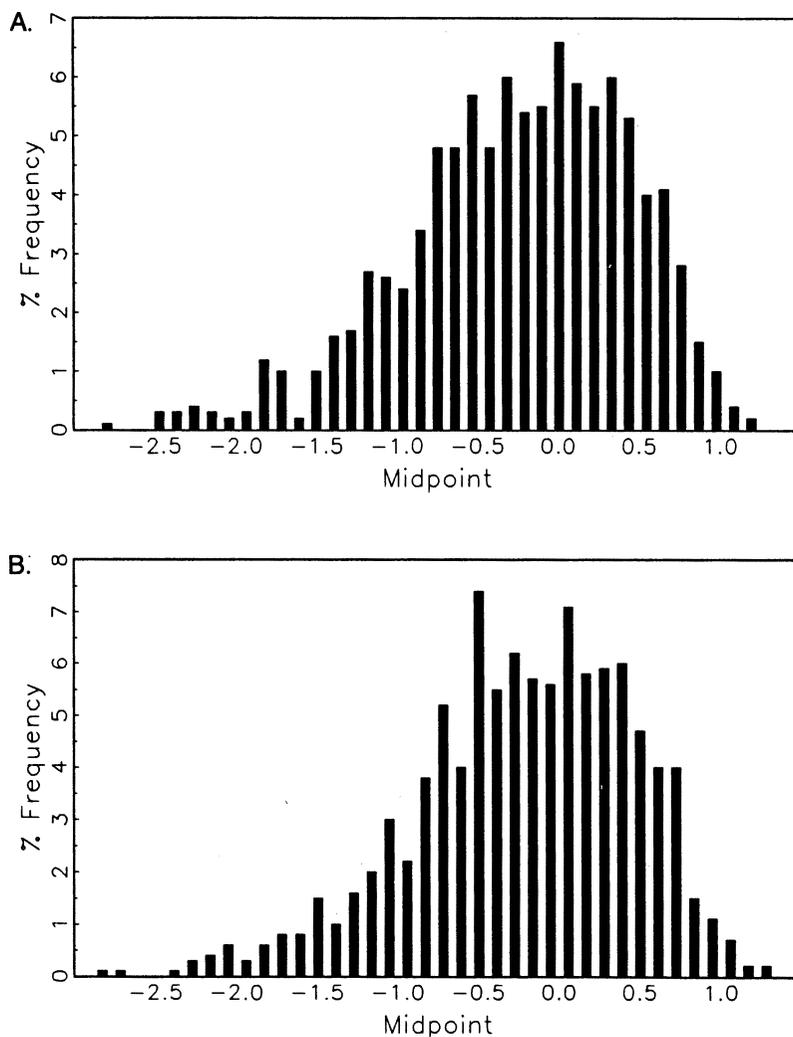
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Notes: Relative volatility is measured (in each sample) by the statistic $(\sigma_{jobc} - \sigma_{jobd})/\bar{\sigma}$, where $\bar{\sigma} \equiv (\sigma_{jobc} + \sigma_{jobd})/2$. The histograms correspond to 1,000 random replications of samples of 200 observations each, with $\delta = 0.3$ and $q = 0.75$.

and job destruction, normalized by the average across all samples of the mean (over time) job creation and job destruction. The second row, on the other hand, reports the results of the same experiment, but for the microeconomic-symmetry case. The conclusion is that, on average across samples, regardless of the microeconomic structure, job destruction is more volatile than job creation. This is confirmed by Figure 4, which depicts the histograms of the difference in the standard deviations of job creation and destruction normalized by the average of these two standard deviations. Figure 4A corresponds to the first row of Table 2, while Figure 4B corresponds to the second
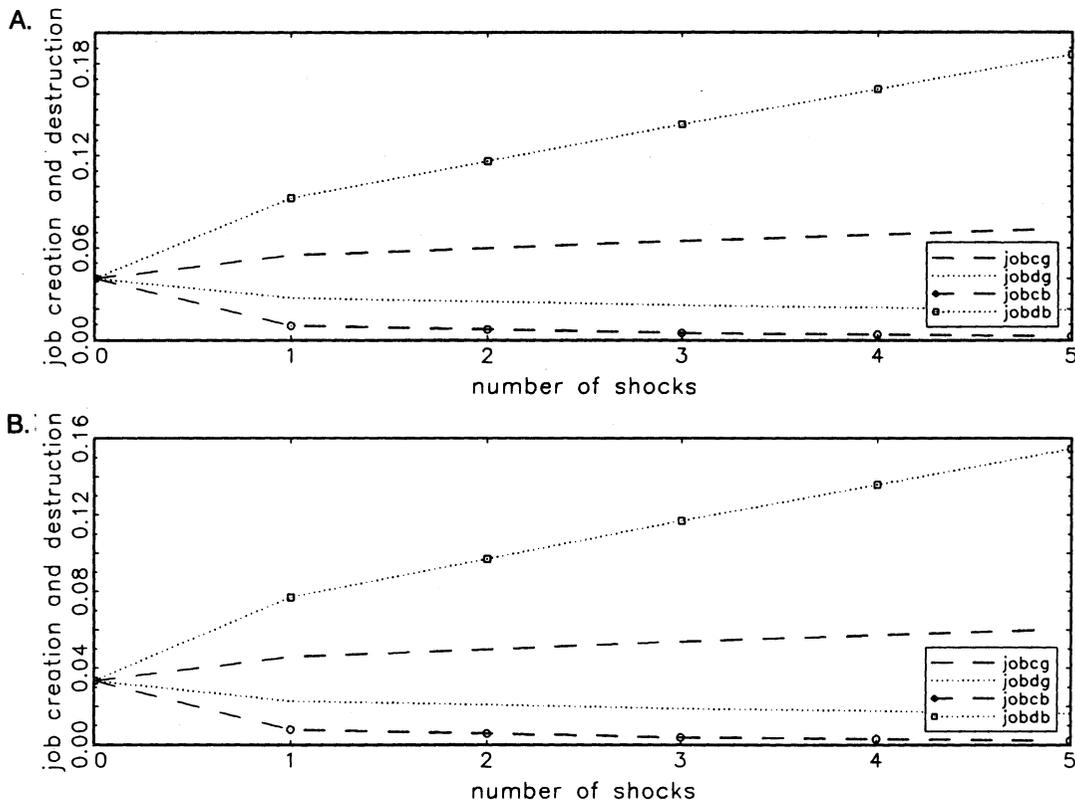
FIGURE 5. JOB CREATION AND DESTRUCTION DURING GOOD AND BAD TIMES: A) ASYMMETRIC
MICROECONOMIC POLICY; B) SYMMETRIC MICROECONOMIC POLICY

Notes: The initial distribution is the ergodic distribution of an individual firm; $\delta = 0.3$ and $q = 0.75$. Asymmetric microeconomic policy: job creation and job destruction (when they occur) are equal to 1 and 6, respectively. Symmetric microeconomic policy: job creation and job destruction (when they occur) are equal to 1.

row of Table 2. Both figures show that there is a larger concentration of observations, especially of extreme ones, to the left of zero (i.e., in the segment where job destruction is more volatile than job creation). Finally, Figure 5 shows aggregate job creation and destruction flows after consecutive positive and negative aggregate shocks starting from a cross-sectional distribution equal to the ergodic distribution of an individual D_i. Figure 5A corresponds to the microeconomic-asymmetry case, while Figure 5B corresponds to the microeconomic-symmetry case. The plain lines depict job creation (dashed) and destruction (dotted) for a sequence of positive shocks, while the lines

with symbols do the same for a sequence of negative shocks. Although this figure must be interpreted with care, in the sense that one should compare strings of positive shocks that are three times longer than the corresponding strings of negative shocks,[15] the asymmetry comes out very clearly: regardless of the microeconomic policy followed by firms, job destruction is more volatile than job creation.

The mechanism generating the aggregate flow asymmetry is intricate, but it illustrates

[15]This is to compare events that have equal probability.

the type of issues that must be considered when working with non-representative-agent models. During good times (which are now most of the times), firms receive, on average, good shocks; this results in more job creation than job destruction. In spite of times being good, however, there is no substantial bunching in the creation decisions, since idiosyncrasies remain important; the standard deviation of each L_i^* given that times are good is $\sigma_{\Delta L^*|g} = 2\sqrt{\lambda_g(1 - \lambda_g)}$, which is 0.98 in the example of Table 2. In those rare times when things turn bad, on the other hand, firms' destruction decisions are synchronized, since idiosyncrasies play only a secondary role; the standard deviation of each L_i^* given that times are bad is $\sigma_{\Delta L^*|b} = 2\sqrt{\lambda_b(1 - \lambda_b)}$, which is only 0.85 in the example of Table 2. When the recovery starts, most firms initiate their journey back to the creation threshold, but they lose synchronization while doing so since idiosyncrasies regain relevance. The consequence of this interplay between the cross-sectional distribution and the business cycle is that job destruction is often more volatile than job creation, as illustrated in the previous figures and table.

These *sample-path* and *synchronization-intensity* explanations of aggregate flow asymmetries are just examples; however, they clearly highlight the interrelation between the endogenous evolution of the cross-sectional distribution of firms and aggregate dynamics. They also show that microeconomic asymmetries might only play a secondary role.

V. Conclusion

This paper should not be interpreted as an argument for the irrelevance of microeconomic stories as explanations of aggregate phenomena. Underlying any cross-sectional story there has to be a microeconomic story. Furthermore, although long episodes of stable stochastic environments disperse firms on the state space so that certain aspects of microeconomic arguments become second-order most of the time, they are not necessarily so always; very large events reshape the cross-sectional distribution and reduce the relevance of ergodic arguments, allowing microeconomic stories to permeate the aggregate more freely. The paper does say, however, that *direct application of microeconomic explanations to aggregate data can be seriously misleading, since they typically do not consider the natural probability forces that tend to undo such explanations.*

To simplify the exposition I have used an extremely stylized model, where microeconomic band policies are very simple and there are no general equilibrium quantity constraints. Although relaxing these assumptions would surely give more realism to the model and may even change the conclusions with respect to the relative importance of fluctuations in one or the other series in the specific examples studied, it would be unlikely to affect the basic insight of the paper. This insight relies only on the stationarity of the departure of actual microeconomic variables from their frictionless optima and on the existence of sufficient heterogeneity; both combined impose strong restrictions on the behavior of aggregate variables. For example, fallacies of composition may also arise when firms face asymmetric *convex* adjustment costs and, therefore, adjust their factors of production or prices continuously but at different speeds in the upward and downward directions. In this example (assuming no drift) firms spend more time in the "slow" than in the "fast" region; thus, the cross-sectional distribution of departures tends to have a larger fraction of firms in the slow region, which implies that the aggregate exhibits substantially less asymmetry in its instantaneous response to positive and negative shocks than do individual firms.

Appendix: Asymmetric Aggregate Shocks

Let

$$\Delta L_{it}^* = \begin{cases} +1 & \text{with probability } \lambda_g \\ -1 & \text{with probability } 1 - \lambda_g \end{cases}$$

if the aggregate has a good realization (v_g),

and

$$\Delta L_{it}^* = \begin{cases} +1 & \text{with probability } \lambda_b \\ -1 & \text{with probability } 1 - \lambda_b \end{cases}$$

if the realization of the aggregate is bad $(-v_b)$.

The aggregate shock is "good" with probability q and "bad" with probability $1 - q$. The no-drift condition then implies

$$v_b = -\frac{q}{1-q}v_g$$

and therefore the standard deviation of the aggregate shock, $\sigma_{\Delta A}$, is equal to

$$\sigma_{\Delta A} = v_g\sqrt{\frac{q}{1-q}}\;.$$

Denoting the relative contribution of aggregate uncertainty to the uncertainty faced by individual firms by $\delta \equiv \sigma_{\Delta A}/\sigma_{\Delta L^*}$, and using the fact that

$$E\left(\Delta L_i^* | v_g\right) = v_g$$

and

$$E\left(\Delta L_i^* | -v_b\right) = -\frac{q}{1-q}v_g$$

yields the expressions used in the paper:

$$\lambda_g = \frac{1}{2}\left(1 + \delta\sqrt{\frac{1-q}{q}}\right)$$

$$\lambda_b = \frac{1}{2}\left(1 - \delta\sqrt{\frac{q}{1-q}}\right).$$

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