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A unified econophysics explanation for the power-law exponents of stock market activity

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Abstract

We survey a theory (first sketched in *Nature* in 2003, then fleshed out in the *Quarterly Journal of Economics* in 2006) of the economic underpinnings of the fat-tailed distributions of a number of financial variables, such as returns and trading volume. Our theory posits that they have a common origin in the strategic trading behavior of very large financial institutions in a relatively illiquid market. We show how the fat-tailed distribution of fund sizes can indeed generate extreme returns and volumes, even in the absence of fundamental news. Moreover, we are able to replicate the individually different empirical values of the power-law exponents for each distribution: 3 for returns, 3/2 for volumes, 1 for the assets under management of large investors. Large investors moderate their trades to reduce their price impact; coupled with a concave price impact function, this leads to volumes being more fat-tailed than returns but less fat-tailed than fund sizes. The trades of large institutions also offer a unified explanation for apparently disconnected empirical regularities that are otherwise a challenge for economic theory.
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1. Introduction

This paper surveys a recent paper [1], in which we present a model in which volatility is caused by the trades of large institutions. This paper may be the first econophysics paper published in a refereed, top-four economics journal. As such, it represents a useful step in the progressive integration of econophysics and economics.[2]

In our theory, spikes in trading volume and returns are created by a combination of news and the trades by large investors. Suppose news or proprietary analysis induces a large investor to trade a particular stock. Since his desired trading volume is then a significant proportion of daily turnover, he will moderate his actual trading volume to avoid paying too much in price impact. The optimal volume will nonetheless remain large enough to induce a significant price change.

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[1]Gopikrishnan's contribution was part of his Ph.D. thesis.
[2]Gabaix et al. [2] presented an early sketch of that theory.

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Traditional measures, such as variances and correlations, are of limited use in analyzing spikes in market activity. Many empirical moments are infinite; moreover, their theoretical analysis is typically untractable. Instead, a natural object of analysis turns out to be the tail exponent of the distribution, for which some convenient analytical techniques apply. Furthermore, there is much empirical evidence on the tails of the distributions, which appears to be well approximated by power laws. For example, the distribution of returns r over daily or weekly horizons decays according to $P(|r|>x) \sim x^{-\zeta_r}$ where ζ_r is the tail or Pareto exponent. This accumulated evidence on tail behavior is useful to guide and constrain any theory of the impact of large investors. Specifically, our theory unifies the following stylized facts:

(i) the power-law distribution of returns, with exponent $\zeta_r \simeq 3$;
(ii) the power-law distribution of trading volume, with exponent $\zeta_q \simeq 1.5$;
(iii) the power law of price impact;
(iv) the power-law distribution of the size of large investors, with exponent $\zeta_S \simeq 1$.

Existing models have difficulty in explaining facts (i)–(iv) together, not only the power-law behavior in general, but also the specific exponents. For example, efficient market theories rely on news to move stock prices and thus can explain the empirical finding only if the news is power-law distributed with an exponent $\zeta_r \simeq 3$. However, there is nothing a priori in the efficient markets hypothesis that justifies this assumption. Similarly, GARCH models generate power laws, but need to be fine-tuned to replicate the exponent of 3.[3]

We rely on previous research to explain (iv), and develop a trading model to explain (iii). We use these facts together to derive the optimal trading behavior of large institutions in relatively illiquid markets. The fat-tailed distribution of investor sizes generates a fat-tailed distribution of volumes and returns (see also Refs. [22–24]). When we derive the optimal trading behavior of large institutions, we are able to replicate the specific values for the power-law exponents found in stylized facts (i) and (ii).[4]

In addition to explaining the above facts, an analysis of tail behavior may have a number of wider applications in option pricing,[5] and risk management.

2. The empirical findings that motivate our theory

This section presents the empirical facts that motivate our theory, and provides a self-contained tour of the empirical literature on power laws.

2.1. The power-law distribution of price fluctuations: $\zeta_r \simeq 3$

The tail distribution of returns has been analyzed in a series of studies that uses an ever-increasing number of data points [3–6]. Let r_t denote the logarithmic return over a time interval Δt. The distribution function of returns for the 1000 largest U.S. stocks and several major international indices has been found to be:[6]

$$P(|r|>x) \sim \frac{1}{x^{\zeta_r}} \quad \text{with } \zeta_r \simeq 3, \tag{1}$$

[3]Also, GARCH models are silent about the economic origins of the tails, and about trading volume.

[4]This includes the relative fatness documented by facts (i), (ii) and (iv) (note that a higher exponent means a thinner tail). Since large traders moderate their trading volumes, the distribution of volumes is less fat-tailed than that of investor sizes. In turn, a concave price impact function leads to return distributions being less fat-tailed than volume distributions.

[5]Our theory indicates that trading volume should help forecast the probability of large returns. Marsh and Wagner [7] provides evidence consistent with that view.

[6]To compare quantities across different stocks, we normalize variables such as r and q by the second moments if they exist, otherwise by the first moments. For instance, for a stock i, we consider the returns $r'_{it} = (r_{it} - r_i)/\sigma_{r,i}$, where r_i is the mean of the r_{it} and $\sigma_{r,i}$ is their standard deviation. For volume, which has an infinite standard deviation, we use the normalization $q'_{it} = q_{it}/q_i$, where q_{it} is the raw volume, and q_i is the absolute deviation: $q_i = \overline{|q_{it} - \overline{q_{it}}|}$.

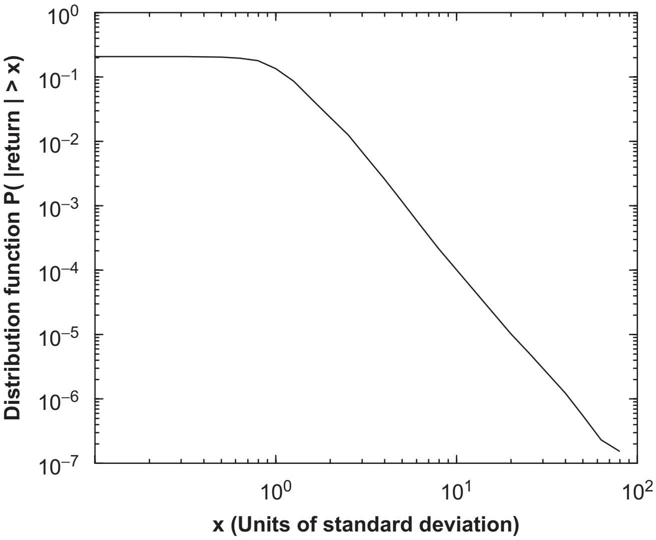

Fig. 1. Empirical cumulative distribution of the absolute values of the normalized 15 min returns of the 1000 largest companies in the Trades And Quotes database for the 2-year period 1994–1995 (12 million observations). We normalize the returns of each stock so that the normalized returns have a mean of 0 and a standard deviation of 1. For instance, for a stock i, we consider the returns $r'_{it} = (r_{it} - r_i)/\sigma_{r,i}$, where r_i is the mean of the r_{it}'s and $\sigma_{r,i}$ is their standard deviation. In the region $2 \leqslant x \leqslant 80$ we find an ordinary least squares fit $\ln P(|r|>x) = -\zeta_r \ln x + b$, with $\zeta_r = 3.1 \pm 0.1$. This means that returns are distributed with a power law $P(|r|>x) \sim x^{-\zeta_r}$ for large x between 2 and 80 standard deviations of returns. Source: Gabaix et al. [2].

with a good fit for $|r|$ between 2 and 80 standard deviations (Fig. 1). OLS estimation yields $-\zeta_r = -3.1 \pm 0.1$, i.e., Eq. (1). We refer to Eq. (1) as "*the cubic law of returns*".[7]

2.2. *The power-law distribution of trading volume: $\zeta_q \simeq 3/2$*

To better constrain a theory of large returns, it is helpful to understand the structure of large trading volumes. Gopikrishnan et al. [8] find that trading volumes for the 1000 largest U.S. stocks are also power-law distributed:[8]

$$P(q>x) \sim \frac{1}{x^{\zeta_q}} \quad \text{with } \zeta_q \simeq 3/2. \tag{2}$$

The precise value estimated is $\zeta_q = 1.53 \pm 0.07$. Fig. 2 illustrates that the density satisfies $p(q) \sim q^{-2.5}$, i.e., Eq. (2). The exponent of the distribution of individual trades is close to 1.5.

To test the robustness of this result, we examine 30 large stocks of the Paris Bourse from 1995–1999, which contain approximately 35 million records, and 250 stocks of the London Stock Exchange in 2001. As shown in Fig. 2, we find $\zeta_q = 1.5 \pm 0.1$ for each of the three stock markets. The exponent appears essentially identical in the three stock markets, which is suggestive of universality.

We refer to Eq. (2) as the "*half-cubic law of trading volume*".

It is intriguing that the exponent of returns should be 3 and the exponent of volumes should be 1.5. To see if there is an economic connection between those values, we turn to the relation between return and volume.

[7]The particular value $\zeta_r \simeq 3$ is consistent with a finite variance, but moments higher than 3 are unbounded. $\zeta_r \simeq 3$ contradicts the "stable Paretian hypothesis" of Mandelbrot [12], which proposes that financial returns follow a Lévy stable distribution. A Lévy distribution has an exponent $\zeta_r \leqslant 2$, which is inconsistent with the empirical evidence [13–15].

[8]We define volume as the number of shares traded. The dollar value traded yields very similar results, since, for a given security, it is essentially proportional to the number of shares traded.

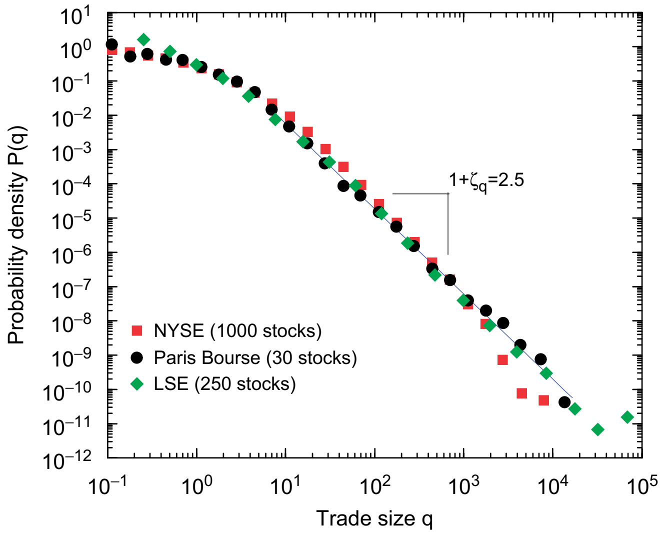

Fig. 2. Probability density of normalized individual transaction sizes q for three stock markets (i) NYSE for 1994–1995 (ii) the London Stock Exchange for 2001 and (iii) the Paris Bourse for 1995–1999. OLS fit yields $\ln p(x) = -(1+\zeta_q)\ln x + \text{constant}$ for $\zeta_q = 1.5 \pm 0.1$. This means a probability density function $p(x) \sim x^{-(1+\zeta_q)}$, and a countercumulative distribution function $P(q>x) \sim x^{-\zeta_q}$. The three stock markets appear to have a common distribution of volume, with a power-law exponent of 1.5 ± 0.1. The horizontal axis shows invidividual volumes that are up to 10^4 times larger than the absolute deviation, $\overline{|q-\overline{q}|}$. Source: Gabaix et al. [1].

2.3. *The power law of price impact: $r \sim V^{\gamma}$*

In Gabaix et al. [1] we present evidence that the price impact r of a trade of size V scales as:

$$r \sim kV^{\gamma}, \tag{3}$$

with $k>0$, $0 \leqslant \gamma \leqslant 1$, which yields a concave price impact function [9–11]. The parameterization $\gamma = 1/2$ is often used, e.g., by Barra [16], Gabaix et al. [2], Hasbrouck and Seppi [10].

Eq. (3) implies $\zeta_r = \zeta_V/\gamma$. Hence, given $\zeta_r = 3$ and $\zeta_V = 3/2$, the value $\gamma = 1/2$ is a particularly plausible null hypothesis. From this relationship, we see a natural connection between the power laws of returns and volumes.

The exact value of γ is a topic of active research. In Gabaix et al. [1], we discuss evidence on the null hypothesis $\gamma = 1/2$. However, it is possible that the true relationship is different, or may vary from market to market. This is why we present a theory with a general curvature γ.

2.4. *The power-law distribution of the size of large investors: $\zeta_S \simeq 1$*

It is highly probable that substantial trades are generated by very large investors. This motivates us to investigate the size distribution of market participants. A power law formulation

$$P(S>x) \sim \frac{1}{x^{\zeta_S}} \tag{4}$$

often yields a good fit. In Gabaix et al. [1], we report estimates consistent with $\zeta_S \simeq 1$, a Zipf's law [17–19].

2.5. *Summary and challenges*

The facts summarized in this section present important challenges. First, economic theories have difficulty in explaining the power-law distribution of returns, as the efficient market theory, and GARCH models, need to be fine-tuned to explain why the distribution of returns would have an exponent of 3.

Second, it is surprising that the Pareto exponent of trading volume is $\zeta_q \simeq 1.5$, while that of institution size is $\zeta_S \simeq 1$. In models with frictionless trading, all agents have identical portfolios and trading policies, except that they are scaled by the size S of the agents (which corresponds to wealth). Hence frictionless trading predicts that the distribution of trading volume of a given stock should reflect the distribution of the size of its investors, i.e., $\zeta_q = \zeta_S \simeq 1$. However, we find that $\zeta_q > \zeta_S$. A likely cause is the cost of trading; large institutions trade more prudently than small institutions, because price impact is monotonically increasing in trade size.

Finally, the basic price impact model [20] predicts a linear relation between returns and volume, which would imply $\zeta_r = \zeta_q$. To explain why ζ_q/ζ_r is close to 1/2, we require a model with curvature of price impact $\gamma \simeq 1/2$. We now present a model that attempts to resolve the above paradoxes.

3. The model

We consider a large fund in a relatively illiquid market. We first describe a rudimentary model for the price impact of its trades. Next, we link the various power-law exponents; this represents the core contribution of this paper. One could employ different microfoundations for price impact without changing our conclusions.

3.1. A simple model to generate a power law price impact

Before presenting, in Section 3.2, the core of the model, we first present a simple microfoundation for the square root price impact. The model used in this section is a formalized version of a useful heuristic argument, sometimes called the "Barra model" of Torre and Ferrari [16].

The model formalizes the compensation required by a liquidity provider to accept a large block of size V. We assume that the liquidity provider has the following mean variance utility function on the total amount W of money earned during the trade:

$$U = E[W] - \lambda[var(W)]^{\delta/2}, \tag{5}$$

with $\lambda > 0$ and $\delta > 0$. The liquidity supplier requires compensation equal to $\lambda\sigma^{\delta}$ to bear a risk of standard deviation σ, i.e., has "δth order risk aversion". With standard mean-variance preferences, $\delta = 2$. In many cases, a better description of what behavior is first-order risk aversion, which corresponds to $\delta = 1$. One justification for first-order risk aversion comes from psychology. Prospect theory [21] presents psychological evidence for this behavior.

In equilibrium, one gets the following price impact function:

$$\tau(V) = HV^{\gamma}, \tag{6}$$

with $H = \lambda\sigma^{\delta}/(3\overline{V})^{\delta/2}$ and

$$\gamma = \frac{3\delta}{2} - 1.$$

In particular, with first-order risk aversion ($\delta = 1$), then $\gamma = 1/2$, a square root price impact of trades.

The proof is in Gabaix et al. [1]. The intuition is that the liquidity provider needs a time $T = V/\overline{V}$ to buy back the V shares. During that time, the price diffuses at a rate σ. Hence the liquidity provider faces a price uncertainty with standard deviation $\sigma\sqrt{T} \sim \sigma\sqrt{V}$. If the liquidity provider is first-order risk aversion, the price concession τ is proportional to the standard deviation, hence $\tau \sim \sigma\sqrt{V}$, i.e., $\gamma = 1/2$.

3.2. The core model: behavior of a large fund

We now lay out the core of our model. The fund periodically receives signals about trading opportunities, which indicate that the excess risk-adjusted return on the asset is $s_t M_t \widetilde{C}$. s_t, M_t and $\widetilde{C}$ are independent. $s_t = \pm 1$ is the sign of the mispricing. M_t is the expected absolute value of the mispricing. M_t is drawn from a distribution $f(M)$, which we assume to be not too fat-tailed.

The model misspecification risk $\widetilde{C}$ captures uncertainty over whether the perceived mispricing is in fact real. $\widetilde{C}$ can take two values, 0 and C^*. If $\widetilde{C}=0$, the signals the fund perceives are pure noise, and the true average return on the perceived mispricings is 0. If $\widetilde{C}=C^*$, the mispricings are real. We normalize $E[\widetilde{C}]=1$.

The fund has S dollars in assets. If it buys a volume V_t of the asset, and pays a price concession $R(V_t)$, the total return of its portfolio is:

$$r_t = V_t(\widetilde{C}M_t - R(V_t) + u_t)/S, \tag{7}$$

where u_t is mean zero noise.

If the model is wrong, expected returns are

$$E[r_t|\widetilde{C}=0] = -V_t R(V_t)/S. \tag{8}$$

We assume that the manager has a concern for robustness. He does not want his expected return to be below some value $-\Lambda$ percent if his trading model is wrong. Formally, this means

$$E[r_t|\widetilde{C}=0] \geqslant -\Lambda. \tag{9}$$

To simplify the algebra, we assume that, subject to the robustness constraint, the manager wants to maximize the expected value of his excess returns $E[r]$.[9] The fund's optimal policy is a function $V(M,S)$ that specifies the quantity of shares V traded when the fund perceives a mispricing of size M. It maximizes the expected returns $E[r_t]$ subject to the robustness constraint (9):

$$\max_{V(M,S)} E[r_t] \text{ s.t. } E[r_t|\widetilde{C}=0] \geqslant -\Lambda, \tag{10}$$

i.e.,

$$\begin{aligned} &\max_{V(M,S)} \quad \frac{1}{S}\int_0^\infty V(M,S)(M - R(V(M,S)))f(M)\,\mathrm{d}M \\ &\text{s.t.} \quad \frac{-1}{S}\int_0^\infty V(M,S)R(V(M,S))f(M)\,\mathrm{d}M \geqslant -\Lambda. \end{aligned}$$

To solve this problem, we use the notation $V(M)$ rather than $V(M,S)$. The Lagrangian is:

$$\begin{aligned} \mathscr{L} &= \int V(M)(M - R(V(M)))f(M)\,\mathrm{d}M - \mu\int V(M)R(V(M))f(M)\,\mathrm{d}M \\ &= \int V(M)(M - (1+\mu)hV(M)^\gamma)f(M)\,\mathrm{d}M. \end{aligned}$$

It is sufficient to optimize on $V(M)$ separately for each M:

$$\begin{aligned} 0 &= \frac{\partial\mathscr{L}}{\partial V(M)} = \frac{\partial}{\partial V(M)}[V(M)M - (1+\mu)hV(M)^{1+\gamma}]f(M) \\ &\to 0 = M - (1+\mu)(1+\gamma)hV(M)^\gamma \\ &\to V(M) = [(1+\mu)(1+\gamma)h]^{-1/\gamma}M^{1/\gamma}. \end{aligned} \tag{11}$$

Thus, using Eq. (8),

$$-E[r_t|\widetilde{C}=0] = E[hV(M)^{1+\gamma}/S] = hE[M^{1+1/\gamma}][(1+\mu)(1+\gamma)h]^{-(1+1/\gamma)}/S.$$

If constraint (9) binds $-E[r_t|\widetilde{C}=0]=\Lambda$. This implies

$$[(1+\mu)(1+\gamma)h]^{-(1+1/\gamma)} = \frac{\Lambda S}{hE[M^{1+1/\gamma}]}$$

[9] One might prefer the formulation $\max_{V(M,S)} E[u(r)]$ subject to $E[u(r)|C=0] \geqslant u(-R)$, with a concave utility u. Fortunately, this does not change the conclusions in many instances, such as $u(r) = -\mathrm{e}^{-\alpha r}$, $\alpha > 0$. On the other hand, with a non-linear function u the derivations are more complex, as they rely on asymptotic equalities, rather than exact equalities. To keep things simple, we use the linear representation (10).

and going back to Eq. (11), we get $V(M) = vM^{1/\gamma}S^{1/(1+\gamma)}$ with

$$v = \left(\frac{\Lambda}{hE[M^{1+1/\gamma}]}\right)^{1/(1+\gamma)}. \tag{12}$$

The expression for R comes from $R = hV^{\gamma}$.

To sum up, we conclude.

Proposition 1. *The optimal policy for a fund of size S perceiving a mispricing of size M is to trade a volume*:

$$V(M, S) = vM^{1/\gamma}S^{1/(1+\gamma)}. \tag{13}$$

The price change after the trade is

$$R(M, S) = hv^{\gamma}MS^{\gamma/(1+\gamma)} \tag{14}$$

for a positive constant v, *which is increasing in* Λ *and decreasing in* h.

It would be greatly desirable to be able to test Proposition 1 directly, for instance by looking at trade-by-trade data in a data set comprising the identity and size of the funds trading. Such a data set is not currently available, but might be in the future. In the meantime, we can already extract some predictions from Proposition 1. By taking the power-law exponents of the last two equations, we find that, if the news is fat-tailed enough (if they have an exponent greater than $(1 + \gamma)\zeta_S$), the following proposition holds.

Proposition 2. *Volumes and returns are power-law distributed, with respective exponents* ζ_V *and* ζ_R *such that*:

$$\zeta_V = (1 + \gamma)\zeta_S, \tag{15}$$

$$\zeta_R = \left(1 + \frac{1}{\gamma}\right)\zeta_S. \tag{16}$$

Indeed, for instance, Eq. (14) gives:

$$\zeta_R = \min(\zeta_M, \zeta_{S^{\gamma/(1+\gamma)}}) = \zeta_{S^{\gamma/(1+\gamma)}} = \frac{1+\gamma}{\gamma}\zeta_S.$$

With the empirical and theoretical baseline case of a square root price impact ($\gamma = 1/2$) and Zipf's law for financial institutions ($\zeta_S = 1$), volumes and returns follow power-law distributions, with respective exponents of 3/2 and 3.

$$\zeta_V = 3/2, \tag{17}$$

$$\zeta_R = 3. \tag{18}$$

These exponents are the empirical values of the distribution of volume and returns.

The above captures our explanation of the origins of the cubic law of returns, and the half-cubic law of volumes. Random growth of mutual funds leads to Zipf's law of financial institutions, $\zeta_S = 1$. The model of Section 3.1 leads to a power law price impact with curvature $\gamma = 1/2$. As large funds wish to lessen their price impacts, their trading volumes are less than proportional to their size. This generates a power-law distribution of the size of trades that is less fat-tailed than the size distribution of mutual funds. The resulting exponent is $\zeta_V = 3/2$, which is the empirical value. Trades of large funds create large returns, and indeed the power-law distribution of returns with exponent $\zeta_r = 3$.

On the other hand, Eqs. (15) and (16) predict that in some circumstances the power laws of volumes and returns will differ from 3/2 and 3. In future research, it would be interesting to evaluate predictions Eqs. (15) and (16) across different stocks, or different stock markets.

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