The Squeaky Wheel Theorem: Why Volatile Sectors Matter Most

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Which Sectors Should You Watch?

Central banks watch GDP. Stock analysts watch earnings. Policymakers debate interest rates. But which sectors of the economy should you *actually* pay attention to?

The answer is counterintuitive: **the ones that bounce around the most**.

Not because volatility is bad. Because volatility reveals which sectors are doing the most work adjusting to shocks. A sector with wild output swings is not misbehaving – it is actively responding to changing economic conditions. A quiet sector is coasting.

This is the core insight behind the **Variance-Response Identity** (VRI), one of the most useful results in the CES framework. It says that you can read the economy's adjustment structure directly from its fluctuations, without building a structural model, running a natural experiment, or estimating deep parameters.

The Squeaky Wheel Analogy

Think about a car with four wheels. One wheel squeaks loudly; the other three are silent. What does the squeak tell you?

It tells you that wheel is bearing load. The squeak (vibration, variance) is not a defect – it is *information*. It reveals which part of the system is under stress and actively absorbing shocks from the road.

Now apply the same logic to an economy with J sectors. Some sectors have highly variable output – semiconductors, construction, durable goods manufacturing. Others are remarkably stable – healthcare, utilities, government services. The VRI says that this pattern is not random. The volatile sectors are the ones with the highest *response* to changing economic conditions. Their variance *is* their importance.

The Identity

The mathematical statement is elegant. Consider an economy at equilibrium, subject to small random shocks. Sector outputs fluctuate around their equilibrium values. The VRI says:

Theorem (Variance-Response Identity).

$$\mathrm{Cov}(x_i, x_j) = T \cdot \chi_{ij}$$

where $\mathrm{Cov}(x_i, x_j)$ is the covariance of output between sectors i and j, T is the level of information friction in the economy, and χ_{ij} is the **response coefficient** – how much sector j's output changes when the effective price in sector i shifts.

In matrix form: $\Sigma = T \cdot \chi$, where Σ is the covariance matrix and $\chi = (\nabla^2\Phi)^{-1}$ is the inverse Hessian of the *CES potential*.

The diagonal case is the punchline:

$$\mathrm{Var}(x_i) = T \cdot \chi_{ii}$$

A sector's variance equals information friction times its own-response coefficient. **Variance is response.**

What Is Information Friction?

The parameter T plays the role of a scale factor. It measures how much randomness the economy faces – or equivalently, how imperfect the information is that agents use to make decisions. Higher T means more friction, larger fluctuations, and noisier signals.

In a world of perfect information ($T = 0$), there would be no fluctuations at all. Every sector would sit exactly at its equilibrium value. In reality, $T > 0$, and the pattern of fluctuations traces out the shape of the economic landscape.

The important point is that T affects all sectors equally. It scales the overall level of variance but does not change the *relative* pattern. If sector A has twice the variance of sector B, then sector A has twice the response coefficient, regardless of the value of T.

Why This Matters: Three Implications

1. Response Matrices From Variance Data Alone

Estimating how the economy responds to shocks is one of the hardest problems in empirical economics. Traditional approaches require structural models with many assumptions, or carefully identified natural experiments. The VRI offers a shortcut: **observe the covariance matrix of output, and you have the response matrix** (up to the scalar T).

This is powerful because covariance matrices are easy to estimate from time series data. You do not need to observe an actual shock to sector i and trace its effect on sector j. You just need to watch both sectors fluctuate and measure how their fluctuations covary.

2. Crisis Variance Is Signal, Not Noise

During economic crises, output variance spikes. The conventional reaction is alarm – volatility is treated as a symptom of disorder. The VRI reframes this: **variance spikes in the sectors that are adjusting fastest**.

When a shock hits, some sectors must reallocate resources, shift production, or adjust prices. These sectors show large output swings. Other sectors, less affected by the shock, remain quiet. The pattern of variance across sectors during a crisis is a real-time map of where adjustment is happening.

This connects to *early warning signals*. As the economy approaches a regime shift, the CES potential landscape flattens ($K_{\text{eff}} \to 0$), and fluctuations grow. The VRI tells you exactly *which* sectors will show the largest pre-crisis variance increases: the ones with the largest response coefficients.

3. Dispersion as a Leading Indicator

Example.

The semiconductor sector is one of the most volatile in the global economy. WSTS data shows that cross-segment dispersion within semiconductors – the spread of growth rates across memory, logic, analog, and other chip categories – systematically leads aggregate economic downturns by approximately 3 quarters.

The VRI explains why. Semiconductors have high χ_{ii} (high own-response), so they show large variance. But more than that, the *internal* dispersion within the semiconductor sector reflects the economy's adjustment dynamics at an early stage, before those adjustments propagate to slower-moving sectors like services or construction.

This is confirmed by the *WSTS dispersion indicator test*, which finds that semiconductor dispersion Granger-causes aggregate output changes with the predicted lead time.

Where Does the Identity Come From?

The VRI is not an assumption. It is a consequence of the CES potential framework.

When the economy sits near a minimum of the CES potential Φ, small shocks push it away from equilibrium. The restoring force is proportional to the curvature $\nabla^2\Phi$ – steep curvature means strong restoring force and small fluctuations; shallow curvature means weak restoring force and large fluctuations.

The balance between random shocks (scaled by T) and restoring force (scaled by $\nabla^2\Phi$) determines the equilibrium distribution of fluctuations. The covariance of that distribution is:

$$\Sigma = T \cdot (\nabla^2\Phi)^{-1}$$

This is the matrix version of a basic insight from (Samuelson1947): at a stable equilibrium, the system's fluctuations are governed by the curvature of the objective function. The CES framework makes this precise by providing an explicit potential whose Hessian can be computed in terms of the curvature parameter K and the sector structure.

The Squeaky Wheel in Practice

The next time you see a sector with high output variance, resist the urge to dismiss it as noisy or unstable. Ask instead: *what is this sector responding to?*

The VRI guarantees that high variance means high responsiveness. The squeaky wheel is not the broken one – it is the one carrying the heaviest load. And if you want to understand where the economy is headed, watch the squeaky wheels. They will tell you first.

References