A Persistence Based Decomposition of Macroeconomic and Financial Time Series

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- Traditional econometrics focuses on the information flow with respect to time evolution, here we explicitly take into account also the flow of information under a change of resolution.
- This paper proposes a linear decomposition of the economic factors as a linear combination of past uncorrelated innovations which are classified by the time of their arrival their level of persistence.
- This non-structural decomposition generalizes the Wold decomposition for stationary time series and the Beveridge-Nelson (1981) permanent transitory decomposition for non stationary integrated ones.

- BN decomposition: Watson (1986), Morley, Nelson and Zivot (2003), Proietti (2006), Oh, Zivot and Creal (2006), and Morley (2011)
- Low Frequency Structural Relations Detection: Muller and Watson (2008) and Muller and Watson (2009).
- Time series multiresolution analysis in economics: Ramsey and Lampart (1998), Gencay and Fan (2008), Gencay and Gradojevic (2009), Gencay, Selcuk and Whitcher (2001), Daubechies (1990), Daubechies (1992), Mallat (1989a) and Mallat (1989b).
- Long Run Risk and Asset Pricing: see the (in)complete list in Ortu Tamoni Tebaldi (2011).

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- Traditional time series representation approach: test the likelihood of a model specification on the finest grid (at the highest resolution) then a model is automatically specified at any coarser resolution by conditioning (temporal aggregation).

Illustration: Time vs Resolution filtration



Degree of persistence and changes of resolution.

- Conditioning under a change of resolution is equivalent to low pass filtering (averaging).
- A measure of persistence is implicitly defined by the resolution filtration.
- Fix minimum resolution scale $h_{\min} = 2^{-J_{\max}} h_{\max}$ then a sequence of resolution scales is defined by $h_j = 2^j h_{\min}$.
- DEFINITION: A shock has degree of persistence j if it is not measurable with respect to the σ-algebra B_{Jmax}-j-1 but measurable at scale of persistence B_{Jmax}-j, i.e. it is removed by j + 1 applications of the filter.

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- Decision Sciences: the preferences of the agents are often horizon dependent (e.g. recursive or hyperbolic preferences, rational inattention).
- Finance: the risk return tradeoff depends heavily on the holding period (long run risks literature)

A linear time series model accounting for persistence.

Definition

The dyadic mean operator acting on the time series of observations up to time t, $\mathbf{x}_t = \{x_{t-k}\}_{k \in 0,..,+\infty}$, is defined by:

$$\pi_{t-k}^{(1)} = \frac{x_{t-k} + x_{t-k-1}}{2}, \quad \pi_{t-2^{j}k}^{(j)} = \sum_{k'=0}^{2^{j-1}} \frac{x_{t-k'-2^{j}k}}{2^{j}}$$

The time series $\pi_t^{d(j)} = \left\{ \pi_{t-2^j k}^{(j)} \right\}_{k \in \mathbb{N}}$ is the j - th (decimated) scale component. Define the detail at scale j, time $t - 2^j k$:

$$\delta_{t-2^{j}k}^{(j)} = \pi_{t-2^{j}k}^{(j-1)} - \frac{\pi_{t-2^{j}k}^{(j-1)} + \pi_{t-2^{j-1}(2k+1)}^{(j-1)}}{2} = \frac{\pi_{t-2^{j}k}^{(j-1)} - \pi_{t-2^{j-1}(2k+1)}^{(j-1)}}{2}$$

The time series $\delta_t^{d(j)} = \left\{ \delta_{t-2^j k}^{(j)} \right\}_{k \in \mathbb{N}}$ is called the *j*-th (decimated) detail component of the time series \mathbf{x}_t .

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The PBD for a stationary process at fixed time t.

Theorem

Consider the PBD of a stationary time series $\{x_{t-k}\}_{k\in\mathbb{N}}$ with Wold decomposition $x_t = \mu + \psi(L)\varepsilon_t$. Then:

• the following decomposition holds for x_t:

$$x_t = \sum_{j=1}^{+J} \delta_t^{(j)} + \pi_t^{(J)}$$
$$\pi_t^{(\infty)} \equiv \lim_{J \to +\infty} \pi_t^{(J)} = \mu$$

the details $\left\{\delta_t^{(j)}\right\}_{j=1}^{+\infty}$ define the term structure of shocks observed at time t.

3 the variance of the rescaled permanent component $\pi_t^{(J)}$ converges to the long run variance.

Example: PBD of consumption growth

Periodogram of differences in log consumption



Figure: PBD of consumption growth.

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Medium Term Business Cycle (Comin Gertler 2006)



Figure: Component 6 of Consumption growth and TFP

- Shocks at scale of persistence j are naturally adapted on a grid with spacing 2^j.
- Forcing their detection at higher frequencies induces spurious correlation effects in the observation
- The instantaneous variance underweights the contribution to long run integrated variance of high persistence components

Definition

The decimated PBD truncated at level J of \mathbf{x}_t is given by the vector $\left(\delta_t^{d(J)}, \pi_t^{(J)}\right)$ where $\delta_t^{d(J)} \equiv \left\{\delta_{t-2^j k_j}^{(j)}\right\}_{j=1,..,J,\ k_j=0,.,2^{J-j-1}}$ and $\pi_t^{(J)}$.

The PBD for an integrated time series

Theorem

Consider $\mathbf{y}_t = \{y_{t-k}\}_{k \in 0,..,+\infty}$ such that $E\left[y_0^2\right] < +\infty$ and $x_t = \Delta y_t$ admit the Wold representation $x_t = \mu + \psi(L) \varepsilon_t$ with $\sum_{j=0}^{+\infty} j\psi_j < +\infty$. Then:

$$y_t - y_0 = \tilde{\pi}_t^{(\infty)} + \sum_{j=1}^{+\infty} \tilde{\delta}_t^{(j)}$$
(1)

where the (stationary) details $\tilde{\delta}_t^{(j)}$ at any level of persistence j and the scale component are given by

$$\begin{split} \widetilde{\delta}_{t}^{(j)} &= -\sum_{k_{j}=0}^{+\infty} \left(\mathcal{T}_{\text{Haar}}^{(\infty)} \widetilde{\psi} \right)_{j,k_{j}} \varepsilon_{j,t-2^{j}k_{j}} \\ \widetilde{\pi}_{t}^{(\infty)} &= \mu t + \psi \left(1 \right) \sum_{s=1}^{t} \varepsilon_{s}. \end{split}$$

Wold Theorem and the PBD.

• Let the Hilbert space (same role of the $\mathcal{H}^{\gamma}(\mathbf{x}_{t})$ space):

$$\mathcal{H}(\mathbf{x}_{t}) = \left\{ Z = \sum_{k \in \mathbb{N}} \alpha_{k} x_{t-k}, \ \left\langle Z^{1}, Z^{2} \right\rangle = \sum_{k \in \mathbb{N}} \alpha_{k}^{1} \alpha_{k}^{2} \right\}$$

metric definition neglects temporal correlations!

• Consider the rescaling operator, $R = D \circ M$ the composition of the dyadic dilation operator D with the dyadic mean M (same role of the L the lag operator). Then:

$$\mathcal{H}(\mathbf{x}_{t}) = \bigoplus_{j=1}^{+\infty} R^{j} \mathcal{W}_{t}^{R} \oplus \mathcal{H}_{t,R}^{(\infty)}$$
$$R^{j} \mathcal{W}_{t}^{R} = \left\langle \delta_{t}^{(j)} \right\rangle, \quad R \mathcal{H}_{t,R}^{(\infty)} \subseteq \mathcal{H}_{t,R}^{(\infty)}$$
(2)

The permanent component (stochastic trend) p_t^{BN} of a unit root non stationary process $x_t = \Delta y_t$ process is that component whose effect is not expected to decay but "persists" at any horizon (resolution scale).

$$p_t^{BN} = y_t + \lim_{h \to +\infty} + E \left[\sum_{k=1}^h \Delta y_{t+k} - \mu h \mid \Omega_t \right]$$
$$= y_t + \lim_{j \to +\infty} E \left[\Delta_{2^j} y_{t+2^j} h_{\min} - \mu 2^j h_{\min} \mid \mathcal{B}_j \cap \mathcal{F}_t \right]$$

hence by CLT for stationary processes:

$$\Delta p_{t}^{BN} \in \mathcal{H}_{t,R}^{(\infty)} = \cap_{j=0,..,+\infty} R^{j} \mathcal{H}_{t}\left(\mathbf{x}\right)$$

Co-integration of Dividends and Prices



Figure: Time series of dividends and prices

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PBD

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Illustration: The scale component and the co-integration of dividends and prices.

Campbell and Shiller log-linear approximation: the permanent components of p_t and d_t are co-integrated with $\beta = [1 - 1]$

- The detail component $\delta_t^{(1)}$ accounts for most of the transitory component.
- Given an integrated process y_t the quantity $\pi_{\lfloor 2^J r \rfloor}^{(J)} / \sqrt{2^J} \Rightarrow \psi(1) \int_0^1 W(r) dr$, we estimate $\pi_{\lfloor 2^J r \rfloor}^{(J)} / \sqrt{2^J}$ using $\frac{1}{T^{\frac{3}{2}}} \sum_{t=1}^T y_{t-1}$.
- The estimated coefficients are consistent with the co-integration relation



Figure: Comparison between BN cycle and the first detail component

BN Trend and Stochastic Scale Component



Figure: A test on the scaling properties of the scale component

GDP and Inflation forecasting

• A test on the predictive content of the transitory components we run the OLS regression of

$$\Delta_h x_{t+h} = \alpha + \sum_{j=1}^J \beta_j x_{t,j} + \epsilon_{t+h}$$
(3)

where $\Delta x_{t+1} = x_{t+1} - x_t$ is the next period change in US GDP and $x_{t,j}$ is the transitory component at level of persistence j.

- Select $x_t = 100 \times \log(GDP_t)$ 1947.q1-2010.q4.
- Select x_t = log (CPI_t/CPI_{t-1}) CPI_t consumer price index seasonally adjusted, January 1947 - December 2008.
- We measure the adjusted R^2 and

$$G(h) = 100 \times \left(1 - \frac{\widehat{MSFE}(h)_{PBD}}{\widehat{MSFE}(h)_{TC}}\right)$$

percent gain in forecast accuracy arising from our suggested decomposition compared to alternative TC (trend-cycle) measures.

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Horse race

Panel A: Final cycle estimates vs. Extended BN

\bar{R}^2	0.15	0.15	0.15	0.15	0.35
Hodrick-Prescott 2-sided					-0.388 (-9.06)
Hodrick-Prescott 1-sided				0.006 (0.062)	
Clark			0.341 (0.43)		
Beveridge – Nelson		1.723 (1.01)			
C ₈					
C ₇	-0.008 (-0.87)	-0.008 (-0.90)	-0.008 (-0.895)	0.557 (1.83)	0.004 (0.489)
<i>C</i> ₆	0.004 (0.16)	0.002 (0.09)	0.006 (0.24)	-0.154 (-0.500)	-0.013 (-0.637)
C ₅	-0.028 (-0.78)	-0.031 (-0.85)	-0.031 (-0.84)	0.255 (0.826)	-0.020 (-0.664)
<i>C</i> ₄	0.031 (0.60)	0.029 (0.56)	0.017 (0.28)	0.273 (0.66)	0.127 (2.79)
<i>C</i> ₃	-0.172 (-2.32)	-0.174 (-2.34)	-0.191 (-2.22)	0.325 (1.382)	0.050 (0.73)
<i>C</i> ₂	0.228 (1.85)	0.227 (1.84)	0.218 (1.74)	0.630 (4.79)	0.462 (4.19)
<i>C</i> ₁	0.568 (3.62)	2.564 (1.29)	0.574 (3.64)	0.186 (1.758)	0.591 (4.34)

Table: Predictive regressions for real GDP growth using lag of cycle estimates.

GDP forecast over multiple horizons



Figure: Adjusted R^2 for GDP forecast over multiple horizons

Gain in GDP forecast accuracy



Figure: Percent gain in GDP forecast accuracy

Inflation forecast over multiple horizons



Figure: Adjusted R^2 for Inflation forecast over multiple horizons

Gain in Inflation forecast accuracy



Figure: Percent gain in Inflation forecast accuracy

A comparison with Core Inflation Cogley (2002)



Figure: Percent gain in Inflation forecast accuracy

- In macroeconomics the study of business cycles begins with the problem of measurement: how to separate macroeconomic data into trends and cycles.
- In finance the risk-return trade-off profile which describes efficient investment opportunities in the market is strongly dependent on the investor's holding period.
- These two areas often address the same issues from different perspectives and languages. Their reconciliation is non trivial and multiresolution approaches seem to be a promising direction!