ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ
ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS
ΣΧΟΛΗ ΟΙΚΟΝΟΜΙΚΩΝ ΕΠΙΣΤΗΜΩΝ SCHOOL OF ECONOMIC SCIENCES
ΤΜΗΜΑ ΟΙΚΟΝΟΜΙΚΗΣ ΕΠΙΣΤΗΜΗΣ DEPARTMENT OF ECONOMICS

Department of Economics

Athens University of Economics and Business

WORKING PAPER no. 18-2025

Long Memory from Cheeger Bottlenecks and Long Cycles in Network Dynamics

Stelios Arvanitis

September 2025

The Working Papers in this series circulate mainly for early presentation and discussion, as well as for the information of the Academic Community and all interested in our current research activity.

The authors assume full responsibility for the accuracy of their paper as well as for the opinions expressed therein.

Long Memory from Cheeger Bottlenecks and Long Cycles in Network Dynamics

Stelios Arvanitis*

September 30, 2025

Abstract

This note develops a spectral–topological foundation for long memory in network autoregressions. We consider AR(1) dynamics driven by the node Laplacian of a sequence of weighted graphs with weakly dependent innovations. Long memory emerges when the near-zero spectrum of the Laplacian is thickened by either of two structural mechanisms: (i) geometric bottlenecks, which trap flows across network cuts; and (ii) topological long cycles with regularly varying distributions, which yield near-harmonic modes. These imply long-memory lower bounds for linear observables and, along with harmonic components, they allow coexistence of random-walk and stationary long-memory behaviors. The framework and could be useful to the design of new applications of network models in economics.

Keywords: Long memory; network autoregression; graph Laplacian; Cheeger bottlenecks; long cycles; simplicial complexes; higher-order networks; econometrics of dependence.

1 Introduction

A time series on $\mathbb{N}$ is said to display long memory if its autocovariance function is not absolutely summable, i.e.

$$\sum_{h=0}^{\infty} |\rho(h)| = \infty.$$

Equivalently, the spectral density has a pole at the origin. This general definition allows for a variety of slowly decaying dependencies. In econometric practice, however, the focus is usually on the case where autocovariances decay at a *hyperbolic* rate, as in the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model (Granger and Joyeux, 1980; Hosking, 1981). If $d \in (0, 1/2)$, then

$$\rho(h) \sim c\, h^{2d-1}, \qquad h \to \infty,$$

*Dept. of Economics, Athens University of Economics and Business, Greece. Email: stelios@aueb.gr

so $d > 0$ corresponds to persistent but stationary dependence. Empirically, long memory has been documented in financial volatility, inflation, interest rates, and macroeconomic aggregates –see among many others (Baillie, 1996; Robinson, 1994).

Beyond purely temporal structures, many economic and financial systems may be partially described by network structures. If L is the Laplacian of a network G, an AR(1) on the graph

$$X_{t+1} = (I - \eta L)X_t + \varepsilon_t, \qquad \eta > 0,$$

propagates shocks along edges; geometry (bottlenecks) and topology (cycles) shape persistence (Chung and Lu, 2006; Schennach, 2018). On fractal graphs, the spectral dimension yields long memory through scale invariance (Schennach, 2018); however, real economic networks are not generally expected to be exact fractals.

In this note, we show that long memory can arise on non-fractal networks via two mechanisms: (i) Cheeger bottlenecks, where multi-scale low-conductance cuts generate a thick near-zero Laplacian spectrum; and (ii) long cycles, where heavy-tailed distributions of cycle lengths produce near-harmonic modes arbitrarily close to zero. Both mechanisms operate directly on graphs without requiring higher simplices. We work with–potentially diverging–sequences of graphs and prove long-memory lower bounds for the dependence of linear observables under short-memory innovations. We also explain why edge-only dynamics on graphs do not generate bottleneck or cycle-related long-memory without higher simplices, and we discuss VARs on simplicial complexes as a natural extension.

Notation and conventions. We write $a_n \asymp b_n$ if a_n/b_n is bounded above and below by positive constants uniformly in n, and $a_n \sim b_n$ if $a_n/b_n \to 1$ as $n \to \infty$. We use $a_h \gtrsim b_h$ to mean that $a_h \geq c\, b_h$ for some constant $c > 0$ independent of h (and similarly $a_h \lesssim b_h$ for an upper bound). For sequences or functions a_n, the notation $a_n = \Theta(b_n)$ indicates that a_n/b_n is bounded away from 0 and ∞ uniformly in n. Weak convergence of finite measures is denoted $\mu_n \rightsquigarrow \mu$. A measurable function $L : \mathbb{R}_+ \to \mathbb{R}_+$ is said to be slowly varying at infinity if $L(cx)/L(x) \to 1$ as $x \to \infty$ for all $c > 0$. A function $R(x)$ is regularly varying at infinity with index ρ if $R(x) = x^\rho L(x)$ with L slowly varying; the exponent ρ is called the index of regular variation–see Bingham et al. (1989).

Further structure. The structure of the remaining note is as follows. Section 2 reviews weighted graphs, Laplacians, and spectral measures. Section 3 defines node-level AR(1) processes built by weakly dependent innovations, linear observables, harmonic / non-harmonic decomposition and shows a spectral representation for autocovariances. Section 4 introduces sequences of graphs and presents the assumption framework which involves a Hilbert-space operator framework with dominated near-zero spectral tails. It also gives sufficient network-related conditions for thick near-zero spectra: Cheeger bottlenecks (geometry) and abundant long cycles (topology), with economic interpretations. Section 5 states and proves the main long-memory lower-bound result. Section 6 discusses potential extensions.

2 Graphs, Laplacians, and Spectral Measures

To study how network geometry and topology shape dynamics, we work with weighted graphs and their Laplacians. Given such a graph, its node Laplacian L_0 encodes diffusion on vertices, while the spectral measure of L_0 describes how linear observables decompose across frequencies. Edge Laplacians and cohomology arise naturally when considering flows and cycles; although they play a secondary role here (since our AR(1) processes live on nodes), it is useful to briefly recall their meaning.

A finite undirected weighted graph is $G = (V, E, w)$ with $V = \{1, \dots, n\}$, $E \subseteq \{\{i, j\} : i \neq j\}$, and weights $w : E \to [0, \infty)$. Write $w_{ij} = w_{ji} > 0$ if $\{i, j\} \in E$ and $w_{ij} = 0$ otherwise. The degree of node i is $d_i = \sum_j w_{ij}$, and $D = \mathrm{diag}(d_1, \dots, d_n)$, $W = (w_{ij})$.

Definition 2.1 (Node Laplacian)**.** *The combinatorial (node) Laplacian is*

$$L_0 = D - W.$$

Equivalently, if B is the weighted incidence matrix with $(Bx)_e = \sqrt{w_{ij}}(x_j - x_i)$ for edge $e = (i, j)$, then $L_0 = B^\top B$.

Since L_0 is real symmetric, the spectral theorem yields a projection–valued measure (PVM) $\Pi_{L_0}(\cdot)$ on $\mathbb{R}$ such that

$$L_0 \;=\; \int_{\mathbb{R}} \lambda \, d\Pi_{L_0}(\lambda), \qquad g(L_0) \;=\; \int_{\mathbb{R}} g(\lambda) \, d\Pi_{L_0}(\lambda),$$

for any bounded Borel function g (the integrals are understood in the strong operator/Bochner sense–see Hall (2013); in finite dimensions they reduce to finite sums. A linear observable is a fixed weight vector $f \in \mathbb{R}^n$ that maps a node state $x \in \mathbb{R}^n$ to the scalar $y = \langle f, x \rangle$ (e.g. $f = e_i$ extracts node i, $f = \mathbf{1}/n$ computes the average, and economic weights encode GDP shares or portfolio holdings). The observable's scalar spectral measure μ_f is the finite Borel measure defined by

$$\mu_f(B) \;=\; \langle f, \Pi_{L_0}(B)\, f \rangle, \qquad B \subset \mathbb{R} \text{ Borel.}$$

Equivalently, if $L_0 = \sum_{j=1}^n \lambda_j P_j$ with orthogonal projectors P_j, then $\mu_f = \sum_{j=1}^n \|P_j f\|^2 \, \delta_{\lambda_j}$. In particular $\mu_f(\mathbb{R}) = \|f\|^2$ (it is a probability measure if $\|f\| = 1$). The spectral calculus identity

$$\big\langle f,\, g(L_0)\, f \big\rangle \;=\; \int_{\mathbb{R}} g(\lambda)\, \mu_f(d\lambda)$$

is then a standard Lebesgue integral with respect to the scalar measure μ_f. In this note we repeatedly use $g(\lambda) = (1 - \eta\lambda)^h$ or $g(\lambda) = e^{-\eta\lambda h}$ to connect dynamics to the near-zero tail of μ_f.

Remark 2.2 (Edge Laplacian L_1 and cycles). Besides the node Laplacian $L_0 = B^\top B$, one can define the *edge Laplacian*

$$L_1 = B B^\top,$$

acting on edge flows rather than node values. Its kernel corresponds to harmonic cycles, i.e. circulations around cycles that have zero divergence at every node. By standard homology theory, $\dim\ker L_1 = \beta_1$ equals the number of independent cycles in the graph. Thus, while L_0 captures diffusion across connected components (β_0), L_1 captures cycle structure (β_1).

3 Dynamics on Nodes and Linear Observables

A stochastic process on a network can be defined either on its *nodes* and/or on its *edges*. In the node case, the state vector $X_t \in \mathbb{R}^n$ assigns to each node $i \in V$ a random value $X_t(i)$ (such as an economic indicator, asset return, or population size), and the Laplacian L_0 governs how shocks diffuse in time across neighboring nodes. In the edge case, a process $Z_t \in \mathbb{R}^m$ assigns values to each edge $e \in E$ (such as flows, bilateral trades, or exposures), and its dynamics can be driven by the edge Laplacian L_1. In this note we focus on node-level processes, while retaining awareness that edge-based processes play an analogous role for flows and circulations.

3.1 (V)AR(1) on nodes with weakly dependent innovations

Fix $\eta > 0$ and a symmetric node Laplacian L_0. Consider

$$X_{t+1} = (I - \eta L_0)X_t + \varepsilon_t, \qquad t \in \mathbb{Z}, \tag{1}$$

where (ε_t) is a mean-zero, weakly dependent vector white noise process with spectral density matrix $\Psi(\lambda)$ continuous at $\lambda = 0$ and uniformly bounded in a neighborhood of 0. Assume $0 < \eta < 2/\|L_0\|$ so that $\rho(I - \eta L_0|_{(\ker L_0)^\perp}) < 1$.

Write the orthogonal decomposition $\mathbb{R}^n = \ker L_0 \oplus (\ker L_0)^\perp$ with projectors P_{har} and $P_\perp$. Then

$$X_{t+1} = P_{\text{har}}X_t + P_{\text{har}}\varepsilon_t \; + \; (I - \eta L_\perp)X_t^\perp + P_\perp\varepsilon_t, \qquad X_t^\perp = P_\perp X_t.$$

On $(\ker L_0)^\perp$, stationarity obtains with the Wold form

$$X_t^\perp = \sum_{j\geq 0}(I - \eta L_\perp)^j P_\perp \varepsilon_{t-j}.$$

On $\ker L_0$ (dimension c), $P_{\text{har}}X_{t+1} = P_{\text{har}}X_t + P_{\text{har}}\varepsilon_t$ is a c-dimensional random walk.

3.2 Linear observables and spectral representation

Let $f \in \mathbb{R}^n$ be a weighting vector and define the scalar observable

$$Y_t = \langle f, X_t\rangle = f^\top X_t.$$

Examples include $f = e_i$ (indicator of node i), uniform f (network average), or economically meaningful weights (GDP shares, portfolio weights). Decompose $f = f_{\text{har}} + f_\perp$ with $f_{\text{har}} \in \ker L_0$.

Lemma 3.1 (Spectral covariance formula)**.** *Let μ_f be the spectral measure of f for L_0, and let $\psi(\lambda)$ be the* scalar *innovation spectrum induced by f (i.e., $\psi(\lambda) = f^\top \Psi(\lambda) f$). If ψ is continuous at 0 and bounded near 0, then for $h \geq 0$,*

$$\mathrm{Cov}(Y_t, Y_{t+h}) = \underbrace{\int (1-\eta\lambda)^h \psi(\lambda)\, \mu_f(d\lambda)}_{\text{non-harmonic component}} + \underbrace{\mathbf{1}_{\{f_{\mathrm{har}} \neq 0\}}\, \mathrm{Var}(\langle f_{\mathrm{har}}, P_{\mathrm{har}} \varepsilon_t \rangle)}_{\text{harmonic random-walk variance increment}} . \tag{2}$$

Proof. On $(\ker L_0)^\perp$, $X_t^\perp = \sum_{j\geq 0} (I - \eta L_\perp)^j P_\perp \varepsilon_{t-j}$. Then, since $P_\perp$ is a projection matrix,

$$\langle f_\perp, X_t^\perp \rangle = \sum_{j \geq 0} \langle (I - \eta L_\perp)'^j f_\perp,\ \varepsilon_{t-j} \rangle.$$

Using the orthogonality of the innovations, and the spectral resolution $L_0 = \int \lambda\, d\Pi_{L_0}(\lambda)$, we have that $(I - \eta L_0)^h = \int (1-\eta\lambda)^h\, d\Pi_{L_0}(\lambda)$, due to the fact that the Laplacian is diagonalisable; then:

$$\mathrm{Cov}(\langle f_\perp, X_t^\perp \rangle, \langle f_\perp, X_{t+h}^\perp \rangle) = \int (1-\eta\lambda)^h \psi(\lambda)\, \mu_f(d\lambda).$$

On $\ker L_0$, $P_{\mathrm{har}} X_{t+1} = P_{\mathrm{har}} X_t + P_{\mathrm{har}} \varepsilon_t$ yields $\mathrm{Var}(\langle f_{\mathrm{har}}, P_{\mathrm{har}} X_t \rangle) = t\, \mathrm{Var}(\langle f_{\mathrm{har}}, P_{\mathrm{har}} \varepsilon_0 \rangle)$. □

The lemma makes evident that the non-harmonic part of the covariance can exhibit hyperbolic behavior as $\lambda \to 0$ only if the spectrum becomes infinite. Then, standard Tauberian-type results would imply that long memory could be facilitated if the spectral measure has a regularly varying behavior near zero, with index not greater than one–see Ch.1 in Bingham et al. (1989). The following section exemplifies those considerations.

4 Graph Sequence and Assumption Framework

We consider a sequence of connected graphs $(G_n)_{n\geq 1}$ with node Laplacians $L_{0,n}$ on $\mathbb{R}^{V_n}$, and observables $f_n \in \mathbb{R}^{V_n}$. The sequential framework could be economically motivated as approximating percolation-type models of network formation–see for example Kantemirova et al. (2018); Zeppini and Frenken (2018). This framework is essential: only as the system size grows can the Laplacian spectrum accumulate near zero densely enough to exhibit regularly varying tails, which in turn generate the power-law covariance decay characteristic of long memory.

The sequence can be mathematically treated by considering as embedded into a common separable Hilbert space H via isometries $\iota_n : \mathbb{R}^{V_n} \hookrightarrow H$ (e.g., standard embeddings into ℓ^2), and write $\widehat{L}_n = \iota_n L_{0,n} \iota_n^*$ and $\widehat{f}_n = \iota_n f_n$. Let μ_{n,f_n} denote the spectral measure of $\widehat{f}_n$ for $\widehat{L}_n$.

We do not assume $\widehat{L}_n$ necessarilly converges to a limit operator–which could represent the node Laplacian of a limit network; instead we only control the *near-zero tails* of spectral measures along weak convergence accumulation points. All graphs are connected so that $\ker L_{0,n} = \mathrm{span}\{\mathbf{1}_n\}$; the scalar observable $Y_t^{(n)} = \langle f_n, X_t \rangle$ may, however, have a nonzero harmonic projection $f_{n,\mathrm{har}}$. In what follows we use the assumption framework below:

Assumption 4.1 (Tail domination). There exists a reference measure ν^* on $[0,\infty)$ such that for any accumulation point μ of (μ_{n,f_n}), one has $\mu([0,\lambda]) \geq \nu^*([0,\lambda])$ for all small $\lambda > 0$.

Assumption 4.2 (Network Regular Variation). As $\lambda \downarrow 0$,

$$\nu^*([0,\lambda]) \sim c\lambda^\beta L(1/\lambda),$$

with $\beta \in (0,1]$ and L slowly varying at infinity (see Bingham et al. (1989)).

Assumption 4.3 (Innovation regularity). The innovation spectra $\psi_n(\lambda) = f_n^\top \Psi_n(\lambda) f_n$ are uniformly bounded, and satisfy $\psi_n(\lambda) \to \psi(0) \in (0,\infty)$ as $\lambda \downarrow 0$.

Assumption 4.1 only requires a common lower bound (in the sense of partial first order dominance) for the near-zero tails along subsequences; 4.2 imposes tail regular variation on that envelope, and 4.3 stipulates short-memory innovations at zero frequency.

4.1 Sufficient Conditions for Network Regular Variation

4.1.1 Geometry: Cheeger bottlenecks

From a geometric perspective, long memory emerges when the network contains narrow bridges or thin cuts across which only a small amount of flow can pass. If a graph is nearly decomposable into large regions pairwise joined by weak links, then a diffusion process will spend long periods trapped within one side before slowly leaking to some other. Spectrally, since such bottlenecks "almost separate disjoint communities inside the network," they could generate close to zero eigenvalues for the Laplacian. Moreover, if these bottlenecks occur in "sufficient abundance", then the distribution of small eigenvalues can have a regularly varying tail. This intuition can be formalized by utilizing measures of conductance:

Definition 4.4 (Conductance and bottlenecks). *For $S \subset V$,* $\mathrm{vol}(S) = \sum_{i\in S} d_i$ *and*

$$\Phi(S) = \frac{\sum_{i\in S,\, j\notin S} w_{ij}}{\min\{\mathrm{vol}(S), \mathrm{vol}(V\setminus S)\}}.$$

For a subset of vertices $S \subset V$, the quantity $w(S,\bar{S}) := \sum_{i\in S,\, j\notin S} w_{ij}$ is the total weight of edges crossing the boundary of S. The term $\mathrm{vol}(S) = \sum_{i\in S} d_i$ aggregates the weight strength of nodes in S. $\Phi(S)$ can therefore represent a bottleneck index; it compares the cross-boundary capacity to the internal mass of the smaller side. A small $\Phi(S)$ means that, relative to the size of the smaller block, very little flow can cross the cut, so a diffusion will tend to be trapped for long periods before leaking across the boundary. Spectrally, such poor diffusion manifests as Laplacian eigenvalues near zero: test functions which are (approximately) constant on each side of the cut have small Dirichlet energy and hence small Rayleigh quotient. Thus, low $\Phi(S)$ may indicate a bottleneck. The following condition specifies what it means for bottlenecks to be abundant in our context:

Condition 4.5 (Abundance of bottlenecks). As $n \to \infty$, there exist pairwise disjoint blocks $S_{n,k} \subset V_n$ such that, for small $x > 0$, the (per-volume) count of blocks with conductance at most x satisfies

$$\frac{\#\{k : \ \Phi(S_{n,k}) \le x\}}{\mathrm{vol}(V_n)} \ \sim \ x^{-\gamma} L_\gamma(1/x), \qquad x \downarrow 0, \quad \gamma \in (0,1],$$

with L_γ slowly varying at infinity.

The display indicates that, per unit volume of the network, the number of conductance disjoint bottlenecks less than or equal to x behaves as a regularly varying function at infinity of $1/x$ when we probe for ever finer and finer bottlenecks ($x \downarrow 0$). The following result links this to spectral regular variation.

Proposition 4.6 (Abundance implies Regular Variation)**.** *Under Condition 4.5, there exists $c > 0$ such that, for all small $\lambda > 0$,*

$$\nu([0,\lambda]) \ \gtrsim \ c\,\lambda^\gamma\, L_\gamma(1/\lambda),$$

where ν denotes the (per-volume) limiting spectral measure of the node Laplacian near 0.

Proof. The proof is based on variational arguments for the generalized Rayleigh quotient for the pair (L_0, D), i.e. the normalized Laplacian.

Define the D–inner product $\langle u, v\rangle_D = u^\top D v$ and the generalized Rayleigh quotient $R_D(f) = (f^\top L_0 f)/(f^\top D f)$. For $f = \mathbf{1}_S$,

$$f^\top L_0 f \ = \ \tfrac{1}{2}\sum_{i,j} w_{ij}(f_i - f_j)^2 \ = \ w(S,\bar{S}), \qquad f^\top D f \ = \ \sum_{i\in S} d_i \ = \ \mathrm{vol}(S).$$

Hence

$$R_D(\mathbf{1}_S) = \frac{w(S,\bar{S})}{\mathrm{vol}(S)} \le \Phi(S),$$

where the inequality uses $\mathrm{vol}(S) \ge \min\{\mathrm{vol}(S), \mathrm{vol}(\bar{S})\}$.

Let $\{S_{n,1}, \dots, S_{n,m}\}$ be disjoint. Then $\{\mathbf{1}_{S_{n,k}}\}_{k=1}^m$ are *D–orthogonal*: $\langle \mathbf{1}_{S_{n,k}}, \mathbf{1}_{S_{n,\ell}}\rangle_D = 0$ for $k \ne \ell$. By the Courant–Fischer min–max principle–see Tao (2012)–for the generalized eigenproblem $L_0 f = \lambda D f$ (equivalently for the normalized Laplacian $\mathcal{L} = D^{-1/2} L_0 D^{-1/2}$), the number of generalized eigenvalues λ not exceeding x is at least the dimension of any D–orthogonal subspace whose vectors all have $R_D(\cdot) \le x$. Since (i) $R_D(\mathbf{1}_{S_{n,k}}) \le \Phi(S_{n,k})$, (ii) using Rayleigh comparison, $(f^\top L_0 f)/(f^\top f) \le \max_i D_{i,i}(f^\top L_0 f)/(f^\top D f)$, and (iii) potentially rescaling by $\max_i D_{i,i}$, it follows that

$$N_n(x) \ \ge \ \#\{k : \ \Phi(S_{n,k}) \le x\},$$

where $N_n(x)$ is the number of eigenvalues $\le x$ for $L_{0,n}$.

Now, let ν_n be the empirical spectral measure of the generalized eigenvalues (normalized by $\mathrm{vol}(V_n)$). Then

$$\nu_n([0,x]) \ \ge \ \frac{\#\{k : \ \Phi(S_{n,k}) \le x\}}{\mathrm{vol}(V_n)}.$$

By Condition 4.5 (interpreted per unit volume) this lower bound is asymptotically $x^{-\gamma} L_{\text{geom}}(1/x)$ as $x \downarrow 0$, which yields the claimed regularly varying lower bound for the limiting measure $\nu([0, x])$. Finally, relabel x as λ to match the statement. □

Remark 4.7 (Interpretation of the Abundance Condition 4.5). In trade/financial networks, $S_{n,k}$ can represent country/sectoral communities linked by few weak ties (sanctions, regulatory frictions, liquidity constraints). Shocks originating in one block dissipate slowly across the boundary because $w(S, \bar{S})$ is small relative to the block's activity $\text{vol}(S)$.

Two (potentially parallel) mechanisms that can produce abundance in percolation frameworks are (i) nested scales, i.e. communities of different sizes, each weakly connected to the rest of the network. (ii) Growing counts: a large number of communities of comparable size, each with low conductance.

4.1.2 Topology: long cycles

Besides bottlenecks, another way to generate near-zero Laplacian eigenvalues is through long cycles.

Definition 4.8 (Cycles in weighted graphs)**.** *In a weighted graph $G = (V, E, w)$, a* cycle *C is a simple closed path $v_1, v_2, \ldots, v_m, v_{m+1} = v_1$ with $\{v_i, v_{i+1}\} \in E$ for all i and no other vertex repetitions. The* length *$|C|$ of the cycle is the number of distinct vertices m it traverses.*

If a graph contains a cycle of length m, then circulation around that cycle produces a test function with Rayleigh quotient of order $1/m^2$. Thus, very long cycles correspond to Laplacian eigenvalues arbitrarily close to zero. If the graph sequence (G_n) contains many long cycles, distributed with a heavy tail in length, then the near-zero spectrum thickens in a regularly varying fashion. Intuitively, flows can circulate around these large cycles for long durations without dissipation, creating "near-harmonic" directions in the Laplacian spectrum and giving rise to long memory in node-level observables.

Now abundance network abundance in long cycles is formalized via the per vertex Cycle length distribution and–dually to the bottlenecks' situation–the control of its right tail:

Definition 4.9 (Cycle length distribution per vertex)**.** *Let $\mathcal{C}_n$ denote the set of simple cycles in G_n. For $m \geq 3$, define the* cycle length tail per vertex *by*

$$F_n(m) \;=\; \frac{1}{|V_n|}\, \#\{C \in \mathcal{C}_n :\; |C| \geq m\}.$$

Condition 4.10 (Heavy-tailed cycle lengths). There exists $\alpha \in (0, 2]$ and a slowly varying function L_α such that, uniformly along subsequences of (G_n),

$$F_n(m) \;\sim\; C\, m^{-\alpha} L_\alpha(m), \qquad m \to \infty.$$

This,[1] along with a condition of boundedness for the sequence of average weights produces the connection between the long-cycles machinery and the spectral regular variation:

Proposition 4.11 (Long cycles imply Regular Variation)**.** *Suppose Condition 4.10 (heavy-tailed cycle lengths) holds, and that as* $n \to \infty$, $\frac{1}{|V_n|}\sum_{(i,j)\in E} w_{i,j} = O(1)$. *Then for small* $\lambda > 0$, *the spectral measure* ν *of the node Laplacian satisfies*

$$\nu([0,\lambda]) \;\gtrsim\; \lambda^{\alpha/2}\, L_\alpha(1/\lambda).$$

Proof. Fix a simple cycle C of length m in G_n. Let $\bar{w}(C) = m^{-1}\sum_{(i,j)\in C} w_{ij}$ denote the average weight along the cycle. Consider the test function f equal to the first Fourier mode on C, namely $f(j) = \cos(2\pi j/m)$ for j in cyclic order, and $f = 0$ elsewhere. Then

$$f^\top L_0 f = \sum_{(i,j)\in C} w_{ij}(f(i) - f(j))^2 = O\!\left(\frac{\bar{w}(C)}{m}\right), \qquad \|f\|^2 = \Theta(m).$$

Hence the Rayleigh quotient satisfies

$$R(f) = \frac{f^\top L_0 f}{\|f\|^2} = O\!\left(\frac{\bar{w}(C)}{m^2}\right).$$

The Courant–Fischer min-max principle then implies that L_0 has an eigenvalue $\lambda \le c\,\bar{w}(C)/m^2$ for some absolute constant $c > 0$. Thus, each cycle of length m contributes an eigenvalue at most $c\,\bar{w}(C)/m^2$. For any $\ell > 0$,

$$\#\{\lambda_j \le \ell\} \;\ge\; \#\big\{C \in \mathcal{C}_n :\; |C| \ge \sqrt{c\,\bar{w}(C)/\ell}\big\}.$$

Normalize by $|V_n|$ to obtain a lower bound for the empirical spectral measure $\nu_n([0,\Lambda])$. Under Condition 4.10 and the boundedness of the sequence of average weights, the cycle length distribution is regularly varying with index α, so the induced distribution of eigenvalues has regularly varying tail with index $\alpha/2$ producing the result. □

Remark 4.12 (Economic interpretation). In economic networks, large cycles may correspond to long chains of interdependence that eventually close on themselves: e.g. production loops in input–output networks, ownership cross-holdings among firms, or multi-country trade circuits. If the distribution of such loops is heavy-tailed, then shocks can circulate for long durations before dissipating, manifesting in fractional long memory for node-level observables.

Conditions 4.5 and 4.10 can hold simultaneously. Then:

Corollary 4.13. *Under both 4.5 and 4.10, Assumption 4.2 holds with* $\beta := \min(\gamma, \frac{a}{2})$ *and* $L := L_{\min(\gamma,\frac{a}{2})}$.

[1] The abundance of long cycles condition is related but not completely determined by the sequence of β_1 (the topological dimensions of the kernels of the edge Laplacians $\ker L_1$); it is the also the magnitudes of those cycles, and their distribution that generates the potential for near-zero eigenvalues of L_0 and drives long memory.

5 Main Result

For each n, let $Y_t^{(n)} = \langle f_n, X_t \rangle$ be the observable, with decomposition $f_n = f_{n,\mathrm{har}} + f_{n,\perp}$ and spectral measure μ_{n,f_n} for $L_{0,n}$.

Theorem 5.1 (Uniform long-memory bounds with and without harmonic parts)**.** *Under Assumptions 4.1–4.3, let $f_n = f_{n,\mathrm{har}} + f_{n,\perp}$.*

*(i) (*Non-harmonic case*) If $f_{n,\mathrm{har}} = 0$, then there exist constants $K_1, K_2 > 0$ (independent of n) such that for all large h,*

$$\mathrm{Cov}\big(\langle f_n, X_t\rangle, \langle f_n, X_{t+h}\rangle\big) \gtrsim h^{-\beta} L(h).$$

*(ii) (*With harmonic part*) If $\|f_{n,\mathrm{har}}\| \not\to 0$, then*

$$Y_t^{(n)} = \langle f_{n,\mathrm{har}}, X_t\rangle + \langle f_{n,\perp}, X_t\rangle = Y_t^{\mathrm{RW}} + Y_t^{\perp},$$

where Y_t^{RW} is a random walk with variance growth $\mathrm{Var}(Y_t^{\mathrm{RW}}) \sim \sigma_{\mathrm{har}}^2 t$ and $Y_t^{\perp}$ is a stationary long-memory process satisfying

$$\mathrm{Cov}(Y_t^{\perp}, Y_{t+h}^{\perp}) \;\gtrsim\; h^{-\beta} L(h).$$

Thus the observable contains both a nonstationary random-walk trend and a stationary long-memory component.

Proof. Step 1. Non-harmonic part. By Lemma 3.1 and $1 - x \geq e^{-x-x^2}$ for $x \in [0, 1/2]$, choose $\varepsilon \leq 1/(2\eta)$ and write

$$\int (1-\eta\lambda)^h \psi_n(\lambda)\, d\mu_{n,f_n}(\lambda) \;\geq\; \inf_{0\leq\lambda\leq\varepsilon} \psi_n(\lambda) \int_0^{\varepsilon} (1-\eta\lambda)^h \, d\mu_{n,f_n}(\lambda).$$

By Assumption 4.3, $\inf_{0\leq\lambda\leq\varepsilon} \psi_n(\lambda) \geq \psi(0)/2$ for all large n, hence

$$\mathrm{Cov}_{\perp}^{(n)}(h) \;\geq\; c_0 \int_0^{\varepsilon} (1-\eta\lambda)^h \, d\mu_{n,f_n}(\lambda), \quad c_0 := \psi(0)/2.$$

Since $(1-\eta\lambda)^h \geq e^{-\eta\lambda h - \eta^2\lambda^2 h} \geq e^{-\eta\lambda h} e^{-\eta^2\varepsilon^2 h}$ on $[0,\varepsilon]$, for fixed ε and large h we have

$$\mathrm{Cov}_{\perp}^{(n)}(h) \;\geq\; c_1 \int_0^{\varepsilon} e^{-\eta\lambda h} \, d\mu_{n,f_n}(\lambda), \quad c_1 := c_0 e^{-\eta^2\varepsilon^2 h}.$$

By Assumption 4.1, $d\mu_{n,f_n} \geq d\nu^*$ on $(0,\varepsilon]$, thus

$$\int_0^{\varepsilon} e^{-\eta\lambda h} \, d\mu_{n,f_n}(\lambda) \;\geq\; \int_0^{\varepsilon} e^{-\eta\lambda h} \, d\nu^*(\lambda).$$

By Assumption 4.2, $\nu^*([0,\lambda])$ is regularly varying with index β. By Karamata's Tauberian Theorem (see Th. 1.7.1 in Bingham et al. (1989)), as $h \to \infty$,

$$\int_0^{\varepsilon} e^{-\eta\lambda h}\, d\nu^*(\lambda) \;\sim\; \tilde{c}\, h^{-\beta} L(h).$$

The asserted lower bound follows with constant $c_1\tilde{c}$.

Step 2. Harmonic part. On $\ker L_0$, the dynamics reduce to

$$P_{\mathrm{har}} X_{t+1} = P_{\mathrm{har}} X_t + P_{\mathrm{har}} \varepsilon_t,$$

which is a vector random walk of dimension $\beta_0 = 1$ (since graphs are connected). Thus $Y_t^{\mathrm{RW}} = \langle f_{n,\mathrm{har}}, X_t \rangle$ is a univariate random walk with variance growth

$$\mathrm{Var}(Y_t^{\mathrm{RW}}) = t \cdot \mathrm{Var}(\langle f_{n,\mathrm{har}}, \varepsilon_0 \rangle) \;\sim\; \sigma_{\mathrm{har}}^2 t.$$

Step 3. Orthogonality. Because P_{har} and $P_\perp$ are orthogonal projections, and the innovation process decomposes accordingly, the random-walk component Y_t^{RW} is orthogonal to the stationary component $Y_t^{\perp}$. Thus no cross-covariance terms appear.

Finally, Case (i) is simply Step 1 with $f_{n,\mathrm{har}} = 0$. Case (ii) combines Step 1 and Step 2 with orthogonality. □

Corollary 5.2 (Stationary long memory under convergence)**.** *Suppose $f_{n,\mathrm{har}} \to 0$ in H, and that $\mu_{f_n} \rightsquigarrow \nu^*$. Then, the limiting observable $Y_t = \langle f, X_t \rangle$ is stationary with*

$$\mathrm{Cov}(Y_t, Y_{t+h}) \;\asymp\; h^{-\beta} L(h), \qquad d = (1-\beta)/2 \in (0, 1/2].$$

Remark 5.3 (Multiple components in accumulation points). If accumulation graphs were allowed to be *disconnected* (here we assume connected), then $\dim\ker L_0$ equals the number of components $c \geq 1$. A scalar observable would pick a particular projection onto $\ker L_0$, yielding (potentially) a sum of independent random-walk components plus a stationary long-memory part. With c fixed across accumulation points, the number of random-walk directions is stable; with varying c, the nonstationary component can change across subsequences.

Remark 5.4 (Semi-parametric estimation of the tail index). In the premises of Corollary 5.2, and if the innovation process is a square-integrable martingale difference, then the semiparametric estimator for the spectral tail index $\beta_T := \frac{1-\widehat{H}_{mq}}{2}$, where $\widehat{H}_{mq}$ is the Hurst exponent estimator defined in Section 4 of Robinson (1994), is weakly consistent, under the Condition B of Robinson (1994). This follows from Assumption 4.2, Theorems 1 and 3 of Robinson (1994), and the triangle inequality.

Remark 5.5 (Mode-dependent diffusion intensities). The previous analysis assumed a scalar step size $\eta > 0$. In that case, the transition eigenvalues are $\theta_j = 1 - \eta\lambda_j$, with λ_j the Laplacian spectrum. Small nonzero λ_j then lead to fractional long memory provided $0 < \eta\lambda_j < 2$, while larger η may push $\eta\lambda_j > 2$ and hence $\theta_j < -1$, producing oscillatory explosiveness.

However, with a scalar η these behaviors are mutually exclusive across modes: one cannot simultaneously observe stationary long memory and explosive components, because all eigenmodes are scaled by the same factor.

Refined constructions allow for mode-dependent diffusion intensities. Let $L_{0,n} = U_n \Lambda_n U_n^\top$ be the spectral decomposition with $\Lambda_n = \mathrm{diag}(\lambda_{n,1}, \ldots, \lambda_{n,|V_n|})$ the eigenvalues diagonal. Define the update

$$X_{t+1}^{(n)} = \Big(I - U_n\, \eta_n(\Lambda_n)\, U_n^\top L_{0,n}\Big) X_t^{(n)} + \varepsilon_t^{(n)},$$

where $\eta_n(\Lambda_n) = \mathrm{diag}(\eta_{n,1}, \ldots, \eta_{n,|V_n|})$ is diagonal in the Laplacian eigenbasis. Equivalently, the autoregressive parameter is $T_n = I - \eta_n(L_{0,n})\, L_{0,n}$ via spectral calculus. The per-mode transition factors are

$$\theta_{n,j} = 1 - \eta_{n,j}\lambda_{n,j}.$$

For an observable f_n, the scalar process $Y_t^{(n)} = \langle f_n, X_t^{(n)} \rangle$ decomposes into independent AR(1) components indexed by j: (i) the case $\lambda_{n,j} = 0$ results into a random walk component, (ii) the case $0 < \eta_{n,j}\lambda_{n,j} < 2$ resulting into stationary long-memory, and (iii) the case $\eta_{n,j}\lambda_{n,j} > 2$ resulting into an oscillatory explosive component. Thus, with general $\eta_n(\cdot)$ (possibly depending on n), the same observable can simultaneously combine, random trends, explosive parts and stationary long memory components. Orthogonality of Laplacian eigenvectors ensures that cross-covariances between the three parts vanish. Economically, allowing mode-dependent $\eta_{n,j}$ models heterogeneous "diffusion intensities" across communities or scales.

6 Discussion and Outlook

The results established in this note demonstrate that long memory in network-based autoregressive dynamics can arise naturally from two structural sources: abundance of geometric bottlenecks and abundance of long cycles. These features manifest themselves as regularly varying spectral tails of the graph Laplacian, leading to hyperbolically decaying autocovariances of node-level observables. The framework we have developed provides a rigorous spectral–probabilistic justification of long memory that does not rely on stylized fractal geometries, but rather on empirically observable features such as conductance profiles and persistence diagrams.

One natural extension is to construct vector autoregressions (VARs) in which the coefficient matrices are drawn from both the node Laplacian L_0 and the edge Laplacian L_1. Such processes couple node-level states and edge-level flows in a single dynamic system. While these constructions can enrich the dynamics by allowing random-walk components associated with harmonic edge flows, they cannot in the graph case generate fractional long memory from edge-based bottlenecks or long cycles. The reason is structural: Cheeger-type bottlenecks and long-cycles effects at the edge level require 2-simplices (triangles) to "trap" flows and create near-zero eigenvalues of L_1. On pure graphs, where only vertices and edges are present, L_1 contributes at most harmonic components, leading to unit-root–like random walks but no long-memory power laws. Hence a VAR system combining L_0 and L_1 on graphs

can generate richer harmonic behavior, but not additional long memory for node observables emanating from those two sources.

The situation changes fundamentally when one moves from graphs to simplicial complexes. In this richer setting, the edge Laplacian L_1 interacts with the face Laplacian L_2, and more generally L_k interacts with L_{k+1}. Long cycles at dimension 1 that are eventually filled by 2-simplices lead to small but nonzero eigenvalues of L_1, which in turn generate regularly varying spectral tails. This construction overcomes the limitation of graph-based VARs, and provides a natural way to extend long long-memory results to higher-order interactions.

From an economic and social perspective, simplicial complexes provide a parsimonious language for modeling multi-agent interactions that go beyond dyads. A 2-simplex can represent a joint venture between three firms, a trilateral trade agreement, or a multilateral alliance. Higher simplices capture even richer coalitions or institutional structures. In such systems, shocks need not diffuse only along bilateral links but may persist and reverberate within higher-order groups, giving rise to long memory through some sort of topological/geometric persistence. By incorporating these higher-order features into dynamic models, we can better account for empirically observed persistence in macroeconomic, financial, and social data.

The analysis here has focused on graph Laplacians and their spectral tails. Extending the framework to simplicial VAR processes potentially raises new technical and empirical challenges, but it may be related to a unified spectral–topological theory of long memory in higher-order networks. We leave these more complicated dynamics in future research.

References

Baillie, R. T. (1996): "Long Memory Processes and Fractional Integration in Econometrics," *Journal of Econometrics*, 73, 5–59.

Bingham, N. H., C. M. Goldie, and J. L. Teugels (1989): *Regular variation*, vol. 27, Cambridge university press.

Chung, F. and L. Lu (2006): *Complex Graphs and Networks*, American Mathematical Society.

Granger, C. W. J. and R. Joyeux (1980): "An Introduction to Long-Memory Time Series Models and Fractional Differencing," *Journal of Time Series Analysis*, 1, 15–29.

Hall, B. C. (2013): *Quantum theory for mathematicians*, Springer.

Hosking, J. R. M. (1981): "Fractional Differencing," *Biometrika*, 68, 165–176.

Kantemirova, M. A., Z. L. Dzakoev, Z. R. Alikova, S. R. Chedgemov, and Z. V. Soskieva (2018): "Percolation approach to simulation of a sustainable network economy structure," *Entrepreneurship and Sustainability Issues*, 5, 502–513.

Robinson, P. M. (1994): "Semiparametric analysis of long-memory time series," *The Annals of Statistics*, 515–539.

Schennach, S. M. (2018): "Long Memory via Networking," *Econometrica*, 86, 2221–2248.

Tao, T. (2012): *Topics in random matrix theory*, vol. 132, American Mathematical Soc.

Zeppini, P. and K. Frenken (2018): "Networks, percolation, and consumer demand," *Journal of Artificial Societies and Social Simulation*, 21, 1.

ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ
ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS
ΣΧΟΛΗ ΟΙΚΟΝΟΜΙΚΩΝ ΕΠΙΣΤΗΜΩΝ SCHOOL OF ECONOMIC SCIENCES
ΤΜΗΜΑ ΟΙΚΟΝΟΜΙΚΗΣ ΕΠΙΣΤΗΜΗΣ DEPARTMENT OF ECONOMICS

Department of Economics
Athens University of Economics and Business

List of Recent Working Papers

2023

01-23 Real interest rate and monetary policy in the post Bretton Woods United States, George C. Bitros and Mara Vidali

02-23 Debt targets and fiscal consolidation in a two-country HANK model: the case of Euro Area, Xiaoshan Chen, Spyridon Lazarakis and Petros Varthalitis

03-23 Central bank digital currencies: Foundational issues and prospects looking forward, George C. Bitros and Anastasios G. Malliaris

04-23 The State and the Economy of Modern Greece. Key Drivers from 1821 to the Present, George Alogoskoufis

05-23 Sparse spanning portfolios and under-diversification with second-order stochastic dominance, Stelios Arvanitis, Olivier Scaillet, Nikolas Topaloglou

06-23 What makes for survival? Key characteristics of Greek incubated early-stage startup(per)s during the Crisis: a multivariate and machine learning approach, Ioannis Besis, Ioanna Sapfo Pepelasis and Spiros Paraskevas

07-23 The Twin Deficits, Monetary Instability and Debt Crises in the History of Modern Greece, George Alogoskoufis

08-23 Dealing with endogenous regressors using copulas; on the problem of near multicollinearity, Dimitris Christopoulos, Dimitris Smyrnakis and Elias Tzavalis

09-23 A machine learning approach to construct quarterly data on intangible investment for Eurozone, Angelos Alexopoulos and Petros Varthalitis

10-23 Asymmetries in Post-War Monetary Arrangements in Europe: From Bretton Woods to the Euro Area, George Alogoskoufis, Konstantinos Gravas and Laurent Jacque

11-23 Unanticipated Inflation, Unemployment Persistence and the New Keynesian Phillips Curve, George Alogoskoufis and Stelios Giannoulakis

12-23 Threshold Endogeneity in Threshold VARs: An Application to Monetary State Dependence, Dimitris Christopoulos, Peter McAdam and Elias Tzavalis

13-23 A DSGE Model for the European Unemployment Persistence, Konstantinos Giakas

14-23 Binary public decisions with a status quo: undominated mechanisms without coercion, Efthymios Athanasiou and Giacomo Valletta

15-23 Does Agents' learning explain deviations in the Euro Area between the Core and the Periphery? George Economides, Konstantinos Mavrigiannakis and Vanghelis Vassilatos

16-23 Mild Explocivity, Persistent Homology and Cryptocurrencies' Bubbles: An Empirical Exercise, Stelios Arvanitis and Michalis Detsis

17-23 A network and machine learning approach to detect Value Added Tax fraud, Angelos Alexopoulos, Petros Dellaportas, Stanley Gyoshev, Christos Kotsogiannis, Sofia C. Olhede, Trifon Pavkov

18-23 Time Varying Three Pass Regression Filter, Yiannis Dendramis, George Kapetanios, Massimiliano Marcellino

19-23 From debt arithmetic to fiscal sustainability and fiscal rules: Taking stock, George Economides, Natasha Miouli and Apostolis Philippopoulos
20-23 Stochastic Arbitrage Opportunities: Set Estimation and Statistical Testing, Stelios Arvanitis and Thierry Post
21-23 Behavioral Personae, Stochastic Dominance, and the Cryptocurrency Market, Stelios Arvanitis, Nikolas Topaloglou, and Georgios Tsomidis
22-23 Block Empirical Likelihood Inference for Stochastic Bounding: Large Deviations Asymptotics Under *m*-Dependence, Stelios Arvanitis and Nikolas Topaloglou
23-23 A Consolidation of the Neoclassical Macroeconomic Competitive General Equilibrium Theory via Keynesianism (Part 1 and Part 2), Angelos Angelopoulos
24-23 Limit Theory for Martingale Transforms with Heavy-Tailed Noise, Stelios Arvanitis and Alexandros Louka

2024

01-24 Market Timing & Predictive Complexity, Stelios Arvanitis, Foteini Kyriazi, Dimitrios Thomakos
02-24 Multi-Objective Frequentistic Model Averaging with an Application to Economic Growth, Stelios Arvanitis, Mehmet Pinar, Thanasis Stengos, Nikolas Topaloglou
03-24 State dependent fiscal multipliers in a Small Open Economy, Xiaoshan Chen, Jilei Huang, Petros Varthalitis
04-24 Public debt consolidation: Aggregate and distributional implications in a small open economy of the Euro Area, Eleftherios-Theodoros Roumpanis
05-24 Intangible investment during the Global Financial Crisis in the EU, Vassiliki Dimakopoulou, Stelios Sakkas and Petros Varthalitis
06-24 Time will tell! Towards the construction of instantaneous indicators of different agent-types, Iordanis Kalaitzoglou, Stelios Arvanitis
07-24 Norm Constrained Empirical Portfolio Optimization with Stochastic Dominance: Robust Optimization Non-Asymptotics, Stelios Arvanitis
08-24 Asymptotics of a QLR-type test for optimal predictive ability, Stelios Arvanitis
09-24 Strongly Equitable General Equilibrium Allocations, Angelos Angelopoulos
10-24 The Greek macroeconomy: A note on the current situation and future outlook, Apostolis Philippopoulos
11-24 Evolution of Greek Tax System, A Survey of Legislated Tax Changes from 1974 to 2018, Panagiotis Asimakopoulos
12-24 Macroeconomic Impact of Tax Changes, The case of Greece from 1974 to 2018, Panagiotis Asimakopoulos
13-24 `Pareto, Edgeworth, Walras, Shapley' Equivalence in a Small Economy, Angelos Angelopoulos
14-24 Stimulating long-term growth and welfare in the U.S, James Malley and Apostolis Philippopoulos
15-24 Distributionally Conservative Stochastic Dominance via Subsampling, Stelios Arvanitis
16-24 Before and After the Political Transition of 1974. Institutions, Politics, and the Economy of Post-War Greece, George Alogoskoufis
17-24 Gaussian Stochastic Volatility, Misspecified Volatility Filters and Indirect Inference Estimation, Stelios Arvanitis, Antonis Demos
18-24 Endogenous Realtor Intermediation and Housing Market Liquidity, Miroslav Gabrovski, Ioannis Kospentaris, Victor Ortego-Marti
19-24 Universal Choice Spaces and Expected Utility: A Banach-type Functorial Fixed Point, Stelios Arvanitis, Pantelis Argyropoulos, Spyros Vassilakis

2025

01-25 Democracy, redistribution, and economic growth: Some evidence from post-1974 Greece, George C. Bitros

02-25 Assessing Downside Public Debt Risks in an Environment of Negative Interest Rates Growth Differentials, Yiannis Dendramis, Georgios Dimitrakopoulos and Elias Tzavalis

03-25 Wicksellian General Equilibrium, Angelos Angelopoulos

04-25 Institutions and Ethics, Angelos Angelopoulos

05-25 General Equilibrium in a Capitalist Economy, Angelos Angelopoulos

06-25 Public investment multipliers revisited: The role of production complementarities, Vasiliki Dimakopoulou, George Economides, and Apostolis Philippopoulos

07-25 The heterogeneous causal effects of the EU's Cohesion Fund, Angelos Alexopoulos, Ilias Kostarakos, Christos Mylonakis, and Petros Varthalitis

08-25 Gaussian Invariant Markov Chain Monte Carlo, Michalis K. Titsias, Angelos Alexopoulos , Siran Liu, and Petros Dellaportas

09-25 Financial Intermediation, Investment, and Monetary Policy, Ioannis Kospentaris and Florian Madison

10-25 Temperature as a premium factor. Insurance incorporating climate change. A comparative case study between Europe and North America, Nomikou-Lazarou Irene

11-25 How High will our Buildings Become? Angelos Angelopoulos

12-25 Emergency Room General Equilibrium, Angelos Angelopoulos

13-25 Updating Density Estimates using Conditional Information Projection: Stock Index Returns and Stochastic Dominance Relations, Stelios Arvanitis, Richard McGee, and Thierry Post

14-25 Measuring Textual Cohesion via Graph Curvature, Weighted Dominance, and Embedding-Based Coherence, Stelios Arvanitis

15-25 Universal Preference Spaces for Expected Utility via a Banach-type Functorial Fixed Point Stelios Arvanitis, Pantelis Argyropoulos, and Spyros Vassilakis

16-25 Planet Earth's General Equilibrium, Angelos Angelopoulos

17-25 Electable and Stable Insiders' Coalition Governments, Tryphon Kollintzas and Lambros Pechlivanos

18-25 Long Memory from Cheeger Bottlenecks and Long Cycles in Network Dynamics, Stelios Arvanitis

ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ

ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

ΣΧΟΛΗ ΟΙΚΟΝΟΜΙΚΩΝ ΕΠΙΣΤΗΜΩΝ
SCHOOL OF ECONOMIC SCIENCES

ΤΜΗΜΑ ΟΙΚΟΝΟΜΙΚΗΣ ΕΠΙΣΤΗΜΗΣ
DEPARTMENT OF ECONOMICS

Department of Economics
Athens University of Economics and Business

The Department is the oldest Department of Economics in Greece with a pioneering role in organising postgraduate studies in Economics since 1978. Its priority has always been to bring together highly qualified academics and top quality students. Faculty members specialize in a wide range of topics in economics, with teaching and research experience in world-class universities and publications in top academic journals.

The Department constantly strives to maintain its high level of research and teaching standards. It covers a wide range of economic studies in micro-and macroeconomic analysis, banking and finance, public and monetary economics, international and rural economics, labour economics, industrial organization and strategy, economics of the environment and natural resources, economic history and relevant quantitative tools of mathematics, statistics and econometrics.

Its undergraduate program attracts high quality students who, after successful completion of their studies, have excellent prospects for employment in the private and public sector, including areas such as business, banking, finance and advisory services. Also, graduates of the program have solid foundations in economics and related tools and are regularly admitted to top graduate programs internationally. Three specializations are offered:1. Economic Theory and Policy, 2. Business Economics and Finance and 3. International and European Economics. The postgraduate programs of the Department (M.Sc and Ph.D) are highly regarded and attract a large number of quality candidates every year.

For more information:

https://www.dept.aueb.gr/en/econ/