Propagation of shocks through the Estonian production network: First empirical findings

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Outline of today's talk

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2. Existing literature
3. Networks and their properties
4. Production networks and macroeconomic fluctuations
5. Estonian B2B network
6. Empirical distribution of the influence vector
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Motivation and research goals

Small open economies such as Estonia tend to exhibit three to five times higher sensitivity to various economic shocks, including common monetary policy shocks, relative to large euro area economies. We study the underlying sources of the elevated macro-volatility in Estonia, specifically the role of the structure of the production network. Theoretical results of Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012) suggest that sizeable aggregate fluctuations may originate from idiosyncratic firm- and sector-specific shocks, depending on the structural characteristics of the production network.

We aim to profile relevant characteristics of the production network of firms in the Estonian economy — which stands out for a large share of micro and small-size firms — and to assess how distribution of firms and their mutual inter-linkages may contribute to propagation of shocks in the Estonian economy. Special considerations are given to the high share of export-import links of Estonian firms with other economies and how shocks propagate through this mechanism into the domestic production network.

In addition, we plan to make a comparative analysis of the pertinent characteristics of the Estonian production network vis-a-vis those of similarly–sized EU countries in the framework of the ESCB ChaMP network.

Existing literature

Theoretical research on the role of firm–level production networks in generating aggregate — that is macroeconomic–scale — fluctuations can be found in di Giovanni, Levchenko and Mejean (2014), in Magerman, Bruyne, Dhyne and van Hove (2016), and in Pastén, Schoenle and Weber (2024). In particular, Magerman, Bruyne, Dhyne and van Hove (2016) show that over 55% of the aggregate volatility of Belgian GDP over the time period 2002–2012 can be attributed to idiosyncratic firm–level shocks amplified by their propagation through the Belgian production network.

Detailed empirical profiling of firm–level production networks for Hungary and Ecuador, along with less detailed overview of B2B networks in about a dozen other countries across the globe, can be found in Bacilieri, Borsos, Astudillo-Estevez and Lafond (2023). In particular, we use their results on the empirical estimates of shock propagation in firm–level production networks for Hungary, Ecuador and Belgium to benchmark our own estimates for Estonia.

A recent survey of this burgeoning literature can be found in Carvalho and Tahbaz-Salehi (2019).

Networks and their properties

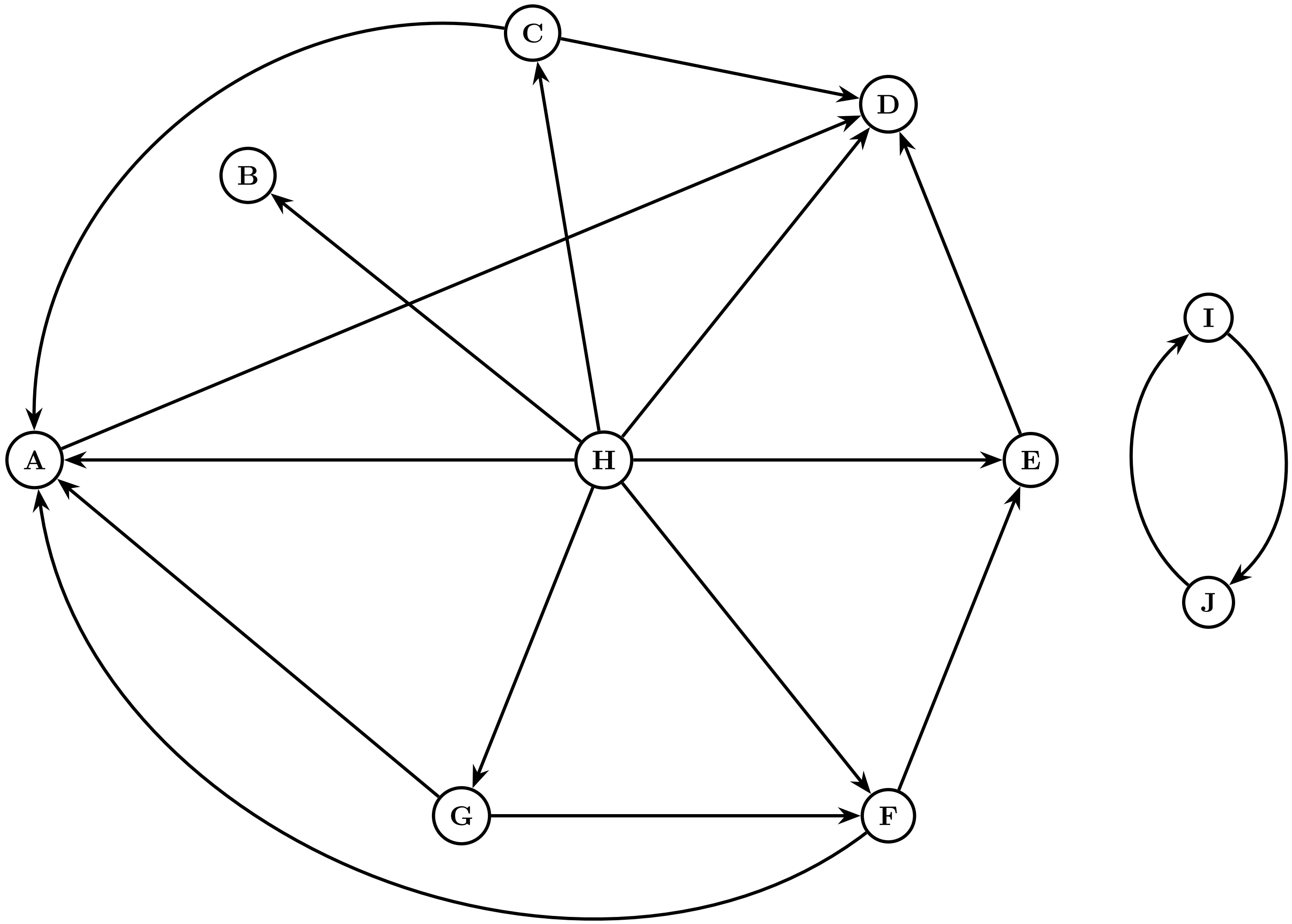
A network, denoted here by $\mathcal{N}$, is the set of *vertices* $\mathcal{V}$ connected by the set of *edges* $\mathcal{E}$, and is formally written as: $\mathcal{N} = \{ \mathcal{V}, \mathcal{E} \}$. Not all vertices may be connected by the edges — such networks are said to be not *fully connected* — and many different *network topologies* are found in natural and social sciences. Networks may further be subdivided into *directed* and *undirected*, depending on the nature of the edges in a network.

Simple mathematical properties of networks are: (i) number of vertices $n := | \mathcal{V} |$, (ii) number of edges $m := | \mathcal{E} |$, and (iii) *mean degree* $\bar{k} := \frac{m}{n}$ is the average number of edges connected to a representative vertex. Distribution of degrees of individual vertices in a network is of particular interest, and in many cases it displays characteristic *heavy tails*.

Some real–world examples of networks are:

- Computer file systems, which are *tree–structured* networks
- Communication networks, which are generally not tree–structured and may have *cycles*
- Social and economic networks, which are usually directed and may have *weighted edges*
- World Wide Web: vertices are web pages, and edges are hyperlinks

Networks and their properties



Production networks and macroeconomic fluctuations

Our theoretical framework is based on the results of Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012), which can succinctly be summarise by the following equation:

$$\sigma_{\text{Aggr}} := \text{stdev}(\, \log \text{GDP}\,) = \sigma \cdot \| \boldsymbol{\lambda} \| \,, \quad \text{where:}$$

σ_{Aggr}	–	aggregate volatility of economy
σ	–	idiosyncratic volatility of a firm–specific productivity shock
$\boldsymbol{\lambda}$	–	vector of Domar weights of firms in the production network a.k.a. *the influence vector*

This expression implies that a particular characteristic of the production network structure — the Euclidean norm of the influence vector $\boldsymbol{\lambda}$ or equivalently the uncentered variance of the distribution of firm–specific Domar weights in the network — determine the amplification of the firm–specific idiosyncratic productivity shocks, which may explain a sizeable share of aggregate volatility of an economy, contrary to the classic Lucas (1977) diversification argument.

Production networks and macroeconomic fluctuations

Under some quite restrictive assumptions on technology and preferences, the firm–specific Domar weights are just equal to firm sales in the overall nominal output of the economy. But in a more general case, the influence vector $\boldsymbol{\lambda}$ can be computed as follows:

$$\boldsymbol{\lambda} = \frac{\alpha}{n} \cdot \left[\, \mathbf{I} - (1-\alpha)\,\boldsymbol{\Omega}\,\right]^{-1} \cdot \mathbf{1}\,, \quad \text{where:}$$

- α – labour share in the production function; assumed to be the same for all firms
- n – number of firms in the economy i.e. the production network size
- $\boldsymbol{\Omega}$ – input–output matrix defined in terms of input expenditures as a fraction of sales

Studies of the real–world production networks have shown that the distribution of $\boldsymbol{\lambda}$ follows the *power law*. Denoting its *scaling exponent* by $1 < \kappa \leq 2$, it can be shown:

$$\sigma_{\text{Aggr}} \sim n^{-\frac{\kappa-1}{\kappa}}\,,$$

which implies that the closer κ is to one, the larger is the share of aggregate volatility that can be attributed to idiosyncratic firm–specific productivity shocks. Thus κ characterises shock propagation in a production network that contributes to macroeconomic volatility.

Estonian B2B network

The Estonian B2B network data is currently around 59 million observations on individual firm–to–firm selling and buying transactions over the time period 2015M1 to 2024M12. All monthly selling and buying transactions over a certain threshold must be reported by law to the Estonian Tax Authorities for VAT enforcement purposes, and these data are now available for research.

The dataset includes pairs of firm IDs, value of sales between firms excluding VAT, value of purchases between firms including VAT, with a separate record of VAT paid on purchases. Sum of transactions between a pair of firms must exceed 1000 EUR in a given calendar month to be reported, but some firms choose to report smaller transactions as well. This reporting threshold has been in place since 2015.

The number of reported monthly transactions has increased from nearly 200 thousand in 2015 to about 315 thousand in 2022-2024 on the selling side, and from 174 thousand to 260 thousand on the buying side. In recent years, there are about 45 to 50 thousand individual firms that submit sales and purchase reports each month.

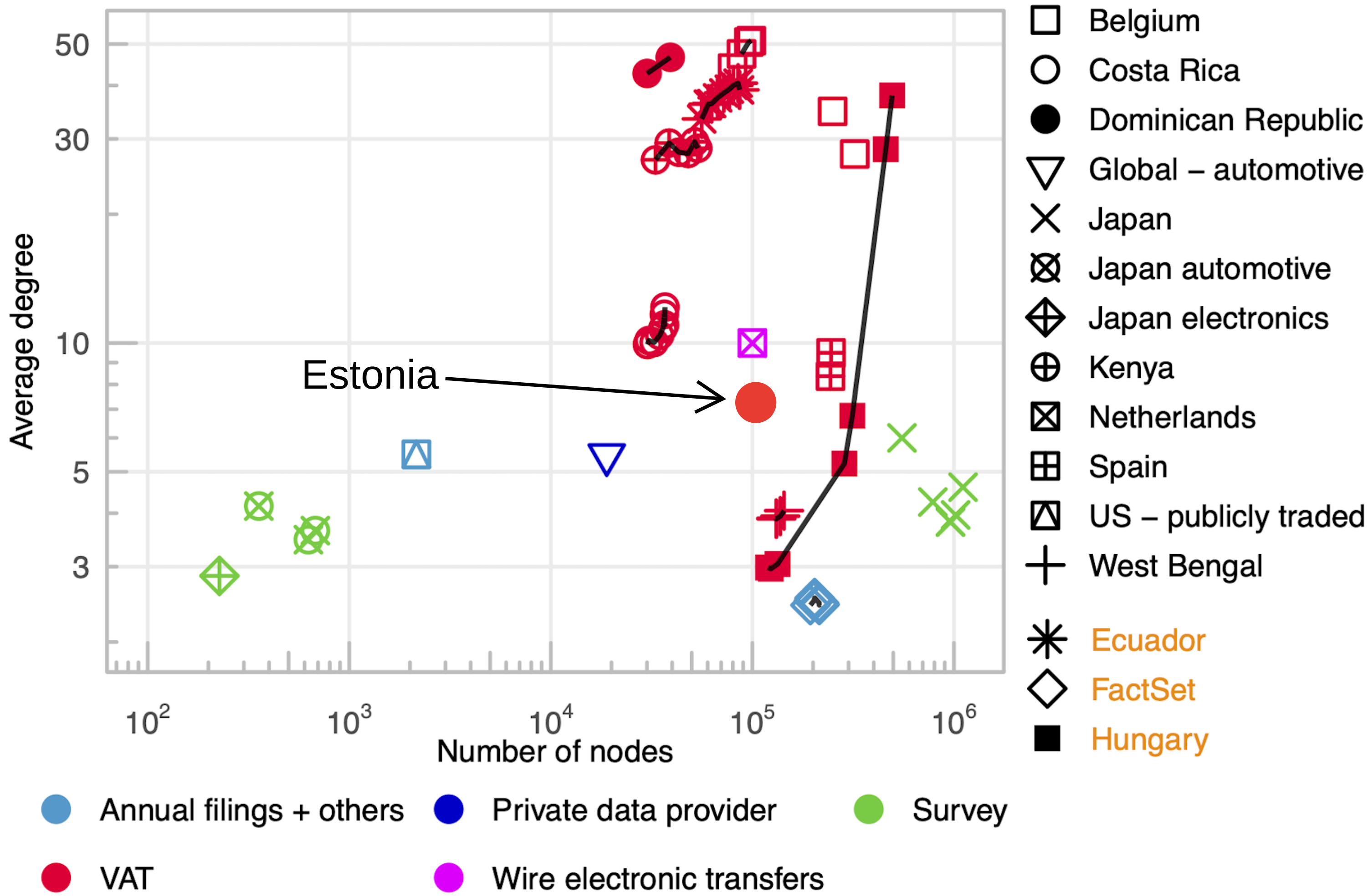
Annual Estonian B2B sales network

$\mathcal{N}$	n	m	$\bar{k}$	$\hat{\kappa}$
2015	90424	717018	7.9295	—
2016	98617	787145	7.9818	—
2017	104877	853066	8.1340	1.4348
2018	108240	889927	8.2218	1.3076
2019	112008	924439	8.2533	—
2020	115549	913387	7.9048	—
2021	122129	1015039	8.3112	1.3836
2022	130268	1130497	8.6782	1.3742
2023	134261	1132325	8.4338	1.3419
2024	135330	1115860	8.2455	—

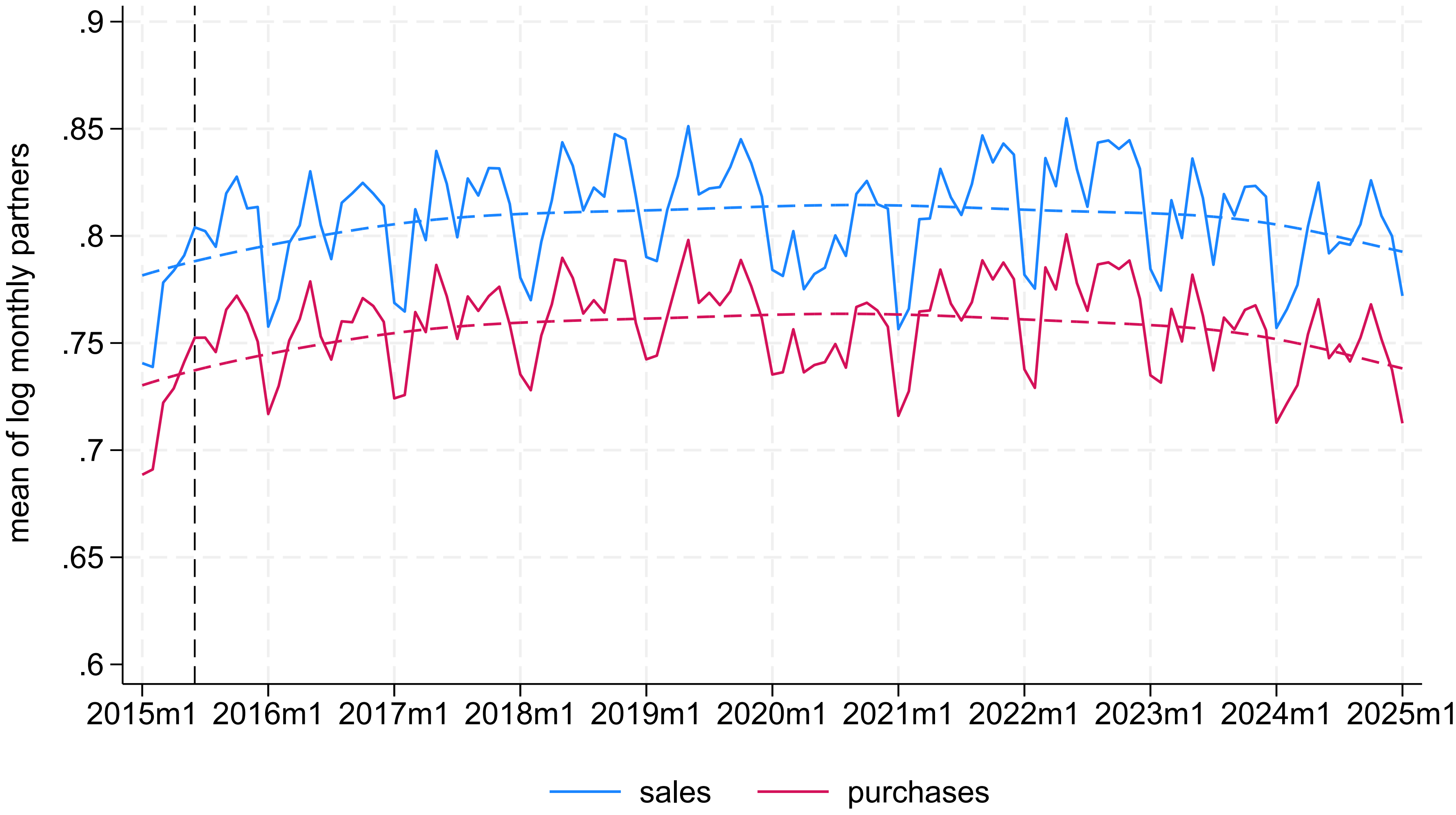
Notes: Empirical network $\mathcal{N}$ properties at the annual aggregation frequency:

n – number of vertices (unique firm IDs)
m – number of edges (sales transactions)
$\bar{k}$ – mean network degree
$\hat{\kappa}$ – scaling exponent estimate

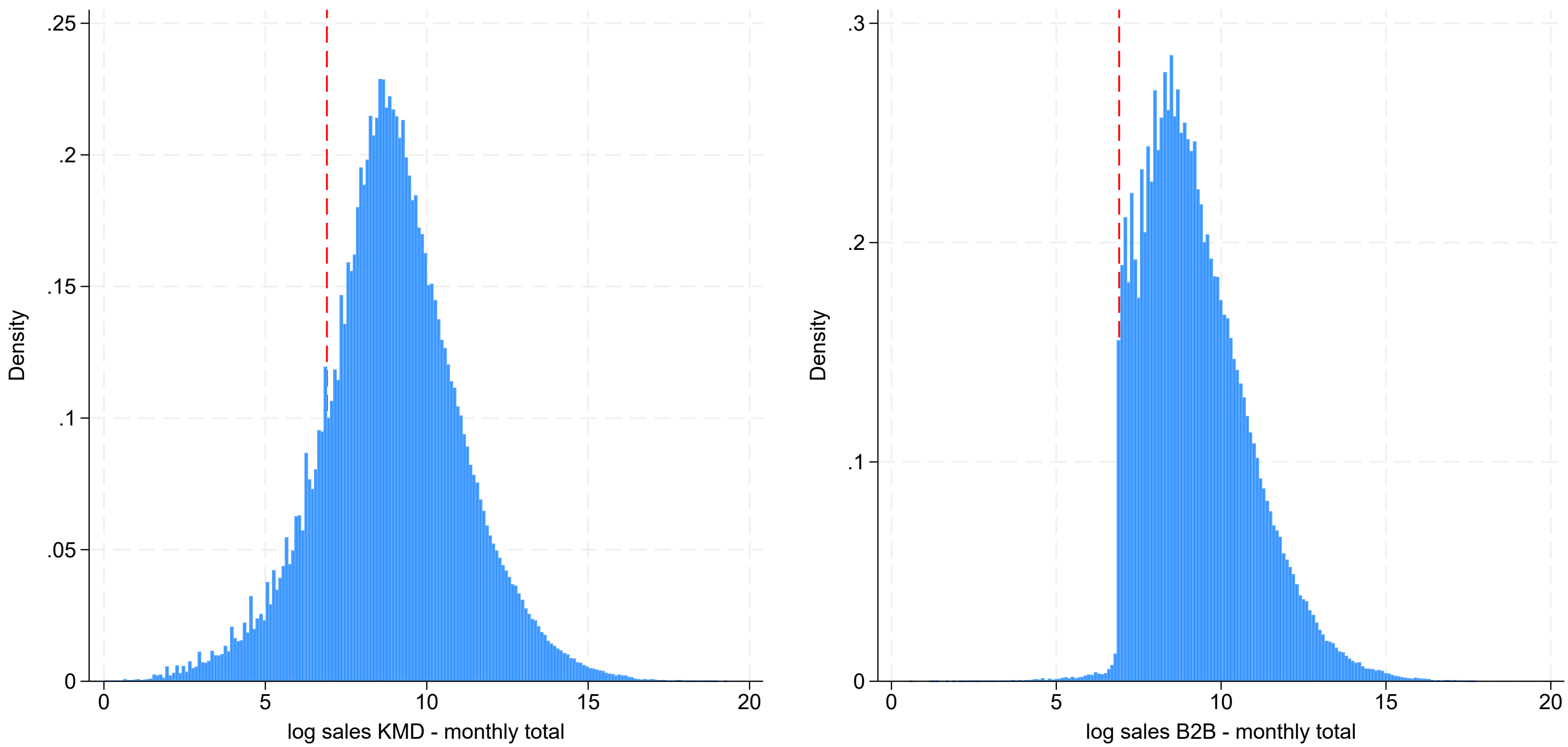
Bacilieri, Borsos, Astudillo-Estevez and Lafond (2023)



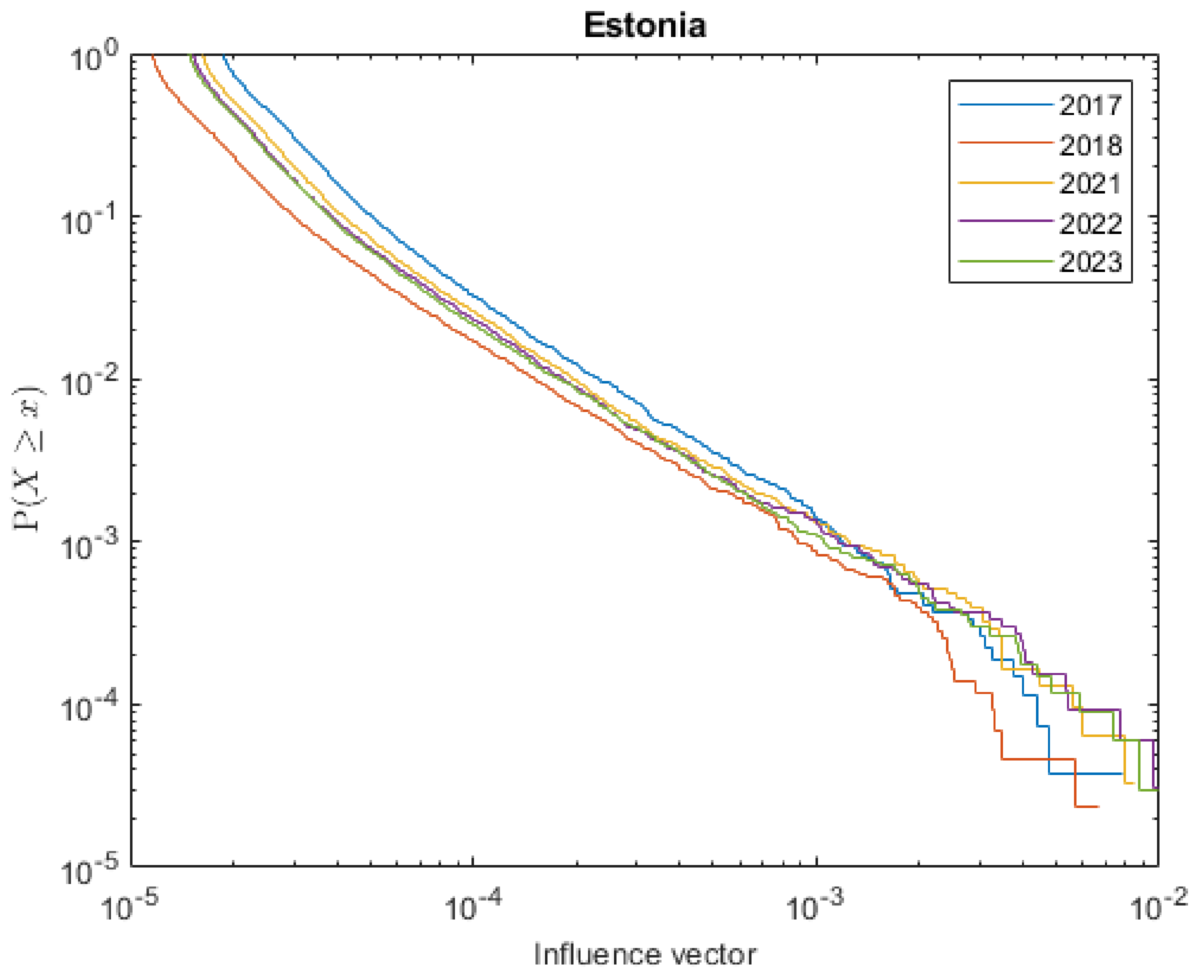
Monthly Estonian B2B network log-degrees



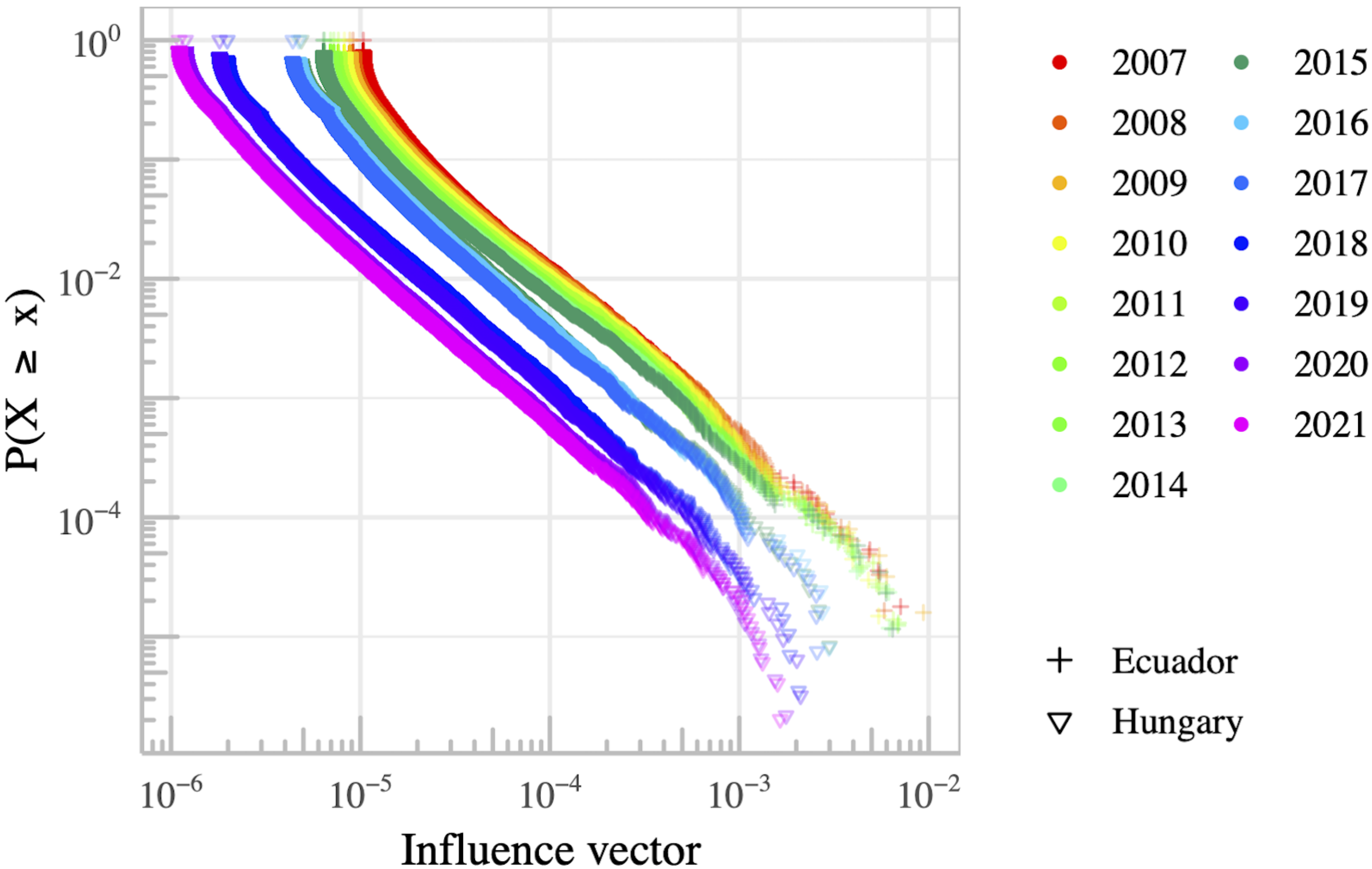
Full log-sales vis-a-vis B2B network log-sales in 2024



Empirical distribution of the influence vector for Estonia



Bacilieri, Borsos, Astudillo-Estevez and Lafond (2023)



Summary and policy implications

- This work is done under the auspices of the ESCB ChaMP Research Netwrok
- We make use of a novel and very large dataset on the B2B network of Estonian firms
- We profile some pertinent characteristics of these data and benchmark these characteristics against the available international evidence
- Using a well–developed theoretical framework, we look at the macroeconomic implications of the production network structure for shock propagation and amplification
- Our (first and preliminary) estimate of the shock propagation parameter (scaling exponent of the influence vector distribution) κ is 1.37 over the sample of five years, which is comparable to a handful available analogous estimates in the literature
- *Monetary policy implication:* Our initial hypothesis that structural characteristics of the Estonian production network lead to heighten sensitivity of the economy to various shocks has, at this point, not been confirmed

Thank you for your attention!