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Nonlinear causal asymmetries in income inequality, corruption, and market power: evidence from OECD nations using symbolic transfer entropy

Nadiah Ruza [a], Fakarudin Kamarudin [a], Hafezali Iqbal Hussain [b,c], M. Ishaq Bhatti [b,d,*]

[a] School of Business and Economics, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia
[b] School of Business and Economics, Universiti Brunei Darussalam, Brunei Darussalam
[c] VIZJA University, Poland
[d] La Trobe Business School, La Trobe University, Melbourne, Australia

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ABSTRACT

This paper examines nonlinear asymmetries in the causal relationships among income inequality, corruption, and market power in OECD countries between 1984 and 2024. It employs a symbolic transfer entropy (STE) framework to overcome limitations inherent in conventional econometrics models. It uses quantile-based binning to represent income inequality, corruption, and market power, ensuring robust performance in the presence of nonnormality and structural variability. Our pooled longitudinal analysis reveals *two dominant asymmetric information flows*: first, market power exerts directional causal influence on income inequality through corruption as a facilitating mechanism; second, corruption exhibits feedback effects that reinforce inequality dynamics. These findings demonstrate that corruption functions as a critical structural mediator linking competitive conditions to distributional outcomes. Beyond its methodological contribution, this study illustrates how information-theoretic approaches can uncover complex, nonlinear interdependencies that are often obscured by traditional methods. Our results show the importance of integrated policy reforms addressing competition policy and governance simultaneously, offering evidence-based guidance for fostering equitable economic growth in developed economies. The discovery that asymmetric and nonlinear feedback are useful for uncovering and decoding complex interdependencies in the economy, the study shows that symbolic transfer entropy can be helpful in policymaking for combined reforms in governance and competition, which can foster more equitable growth.

1. Introduction

Income inequality remains a persistent issue across OECD nations despite stable economic growth and relatively strong institutional development. While the traditional Kuznets hypothesis suggests that inequality should decline after economies reach advanced stages of development, empirical evidence indicates that many OECD economies continue to experience persistently high, and in some cases rising, levels of inequality (Piketty, 2014; Chancel & Piketty, 2021). At the same time, the market structure has also changed

* Corresponding author at: School of Business and Economics, Universiti Brunei Darussalam, Brunei Darussalam.
E-mail address: i.bhatti@latrobe.edu.au (M.I. Bhatti).

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significantly. The growing mark-ups, the heightened concentration of firms, and the emergence of "super-star" firms indicate that the market's power is becoming an even greater distributional force (Autor et al., 2020; De Loecker & Eeckhout, 2025). Such tendencies pose important questions concerning the overlap of market structure, governance, and inequality. Namely, does concentrated economic power equate to political power, and can institutions be captured in ways that weaken competitive conditions and distort regulatory enforcement (Stiglitz, 2015; Acemoglu & Robinson, 2013). At the same time, governance vulnerabilities persist even in many OECD countries, and corruption, regulatory capture, and weakened accountability frameworks facilitate rent-seeking incentives among dominant market participants. This weakens the effectiveness of redistributive policies and enables structural distortions (Gupta, Davoodi & Alonso-Terme, 2002; Jong-Sung & Khagram, 2005).

Recent evidence also suggests that the relationship between corruption, institutional quality, and inequality may vary across different stages of development. Parsons and Rabhi (2025), for example, find that corruption and informal economic activity can exhibit heterogeneous distributive effects across lower- and higher-income institutional environments. Their findings support a "sand in the wheels" interpretation in relatively stronger institutional settings, where corruption weakens institutional effectiveness and contributes to adverse distributive outcomes. This distinction is particularly relevant in the context of OECD economies, where corruption is more likely to operate through institutional and regulatory channels rather than informal petty exchanges.

Although a growing body of research documents correlations among income inequality, corruption and market power, the direction of causation remains opaque. Most empirical work relies on linear, parametric techniques such as VAR, OLS, and GMM (. Past research also focuses on pairs of variables such as inequality–corruption (Li, Xu & Zou, 2000) or market power–inequality (Autor et al., 2020), thereby neglecting the triadic interplay of inequality, corruption and market power. Further, structural breaks, nonlinearities and asymmetries prevalent in long-run panel data are often ignored. Few studies apply information-theoretic or entropy-based tools to long-horizon OECD panels, leaving unresolved whether the flow of influence runs from market power to corruption to inequality, or in alternative directions.

Theoretically, political economy frameworks emphasise that market power enables rent-seeking and policy capture, while institutional economics highlights how weak governance allows monopolistic structures to persist. An augmented Kuznets–governance hypothesis also suggests that governance quality mediates the relationship between development and income distribution (Ahluwalia, 1976; Chong & Calderon, 2000; North, 1990). Together, this triad implies a systemic loop where concentrated market structure fosters corruption, which undermines institutions, thereby increasing inequality. High inequality inturn can reinforce elite capture and further entrench market power.

To address these gaps in the literature, this paper examines the causal asymmetric dynamics between income inequality (INEQ), corruption (CORR) and market power (MP) across OECD countries over the period 1984–2024. Using symbolic transfer entropy (STE) as an information-theoretic, nonlinear, and model-free measure of directional dependence (Camacho, Romeu & Ruiz-Marín, 2021), this study measures directional information flows among all pairs of INEQ, CORR, and MP. This study also identifies dominant causal pathways through Net-Transfer Entropy (Net-TE) and explores country-specific heterogeneity in causality patterns. The contributions are threefold. First, the application of an enhanced STE-Net-TE framework to macro-institutional relationships. Second, the discovery of causal structure in the relationship between inequality, corruption, and market power in one unified empirical structure. Last, policy-oriented insights on the priority of governance and competition reforms to achieve more equitable results.

The focus on OECD economies is intentional rather than purely data-driven. While corruption and inequality challenges are often more visible in developing economies, OECD countries provide an important institutional setting for examining how market concentration, governance quality, and distributive outcomes interact within relatively mature economic systems. In advanced economies, corruption is less likely to manifest through informal petty exchanges and more likely to operate through institutional, regulatory, and structural channels. This allows the present study to isolate nonlinear and asymmetric macro-institutional dynamics within comparatively stable governance environments, where persistent inequality and rising market concentration remain significant policy concerns despite advanced stages of economic development. Moreover, the relatively high institutional comparability across OECD members improves the suitability of pooled longitudinal STE analysis by reducing extreme structural heterogeneity across cross-sectional units.

The rest of the structure of this paper is as follows. In the next section, a brief literature review is presented on the interconnectiveness between INEQ, CORR, and MP under the STE-Net-TE framework. In section 3, we develop asymmetric dynamics linking income inequality and corruption employing a nonlinear information-theoretic framework model. Section 4 presents pooled longitudinal STE analysis with the Net-TE values of the selected variables: INEQ, CORR, and MP in OECD countries. The analysis is done using equal-frequency symbolic binning with the calculations of pooled conditional entropies to understand the combination of the STE and Net-TE, their direction, and the value of the information flows between the selected three variables in the pooled and country-specific levels. The final section contains some concluding remarks.

2. Review of literature

Income inequality, corruption, and market power have increasingly become central themes in contemporary political economy. Thus, they have come to be seen as a dynamic and interdependent force in economic and institutional paths. The existing state of inequality in OECD economies is not the result of technological change or globalization, but also the indication of deeper institutional imbalances that enable individuals with higher economic or political status to seize disproportionate amounts of income and opportunity (OECD, 2021). Recent research highlights that the reinforcing mechanisms that contribute to the growth of inequality, loss of redistributive efficiency, and capture-prone governance are corruption and corporate concentration (Dincă and Strempel, 2025; De Loecker, Eeckhout & Unger, 2020). The empirical data indicate that the level of income inequalities is unprecedented. At least in the past decades, the wealthiest 10% of OECD inhabitants made almost tenfold the revenue of the poorest 10% in 2013, compared to seven times in the 1980s. Autor et al. (2020) and Diez, Leigh, and Tambunlertchai (2018) relate this prolonged expansion of inequality to the rise of the so-called superstar companies and rising corporate markups, which lower wage shares and concentrate wealth levels.

The inequality-corruption nexus is one of the areas of empirical debate. Most studies have shown that the two are reinforcers. Corruption functions as a regressive redistributive mechanism by reallocating resources toward politically connected groups, thus exacerbating income inequalities (Gupta, Davoodi & Alonso-Terme, 2002). Corruption among high-income economies is less likely to be bribery than institutionalised, i.e., lobbying, revolving-door, or preferential treatment, providing preferential advantages to politically connected organisations and individuals (Keneck-Massil, Nomo-Beyala & Owoundi, 2021; Dincă & Strempel, 2025). On the other hand, high levels of inequality contribute to corruption by undermining civil trust, shaping rent-seeking incentives, and permitting tolerance to engage in illicit behaviour (Policardo et al., 2019). OECD data analysis on panels ensures that the causality is two-way. The increase in inequality is pre-empted by corruption, and corruption, in turn, exacerbates the inequality (Parsons & Rabhi, 2025). Importantly, Parsons and Rabhi (2025) demonstrate that the corruption–inequality nexus operates differently across development levels. While corruption acts as 'sand in the wheels' in developed economies, its interaction with the underground economy in developing countries follows distinct mechanisms. This finding reinforces our conceptualization of corruption as a structural mediator in the OECD context, where institutionalized forms of corruption, such as lobbying, revolving-door arrangements, and preferential treatment, function as persistent 'sand in the wheels' that undermine equitable distributional outcomes. Parsons (2025) further emphasizes that economic freedom moderates the corruption–inequality relationship, suggesting that the institutional quality embedded in OECD frameworks shapes how corruption translates into distributional consequences. This feedback is nonlinear and intensifies as inequality passes beyond critical levels, which is supported by quantile and threshold models. Thus, this shows that the marginal effect of corruption is most powerful in highly unequal contexts (Hartwig & Sturm, 2025). The relationship between corruption, institutional quality, and inequality may differ across institutional and developmental contexts. Parsons and Rabhi (2025), for example, show that corruption and informal economic activity can generate heterogeneous distributive effects across lower- and higher-income settings. In weaker institutional environments, certain forms of corruption may temporarily ease access to constrained resources, consistent with the "grease in the wheels" hypothesis. However, in relatively stronger institutional environments, corruption is more consistent with a "sand in the wheels" interpretation, where institutional effectiveness is weakened and distributive distortions intensify. This distinction is particularly relevant for the present study, which focuses on OECD economies characterized by relatively mature institutional systems. Relatedly, Parsons (2025) highlights how institutional and economic-freedom conditions shape corruption dynamics in developing economies, reinforcing the broader argument that corruption mechanisms are context-dependent across institutional environments.

Similar developments connect corruption and market power. The rents brought by monopolistic and oligopolistic systems become an invitation to corruption since the large firms may buy political favors or other regulatory privileges to maintain their status (Ades & Di Tella, 1999; Troesken, 2007). Basihos (2025) demonstrates that advanced democracies experience decreased competition, causing greater corruption within institutions. Corporations turn economic power into political control by financing campaigns, lobbying, and other subtle influences to undermine accountability in democracies. This legalised corruption is a grey area between market efficiency and regulatory capture. Meanwhile, the traditional perspective is made more complicated by the contribution of theory. Varvarigos and Stathopoulou (2023) show that with low-governance environments, more competition can actually increase corruption. Companies can bypass the system by bribing the officials, and with an increase in the level of competition, the number of bribes spreads even more. Therefore, the issue surrounding competition and corruption is situational, based on institutional integrity.

The very existence of market power has significant inequality implications. Under conditions of firms with pricing and wage-setting power, they are able to consume a bigger portion of value added and reassign the income of employees to the owners of capital (Cairó et al., 2025). De Loecker, Eeckhout, and Unger (2020) record that the markups in the world have been increasing exponentially since the 1980s. This has been accompanied by a decrease in the share of income of labor. Autor et al. (2020) associate this with the dominance of very productive superstar firms, the role of which in aggregate inequality grows despite the slowdown in productivity growth. Impullitti and Rendahl (2025) attribute this trend to the $r > g$ mechanism of Piketty (2014). The mechanism states that rising market power elevates returns on capital while suppressing wage and productivity growth, expanding the wealth gap between owners and workers. According to empirical models, one-quarter of the growth in income inequality of advanced economies is potentially due to rising concentration (Cairó et al., 2025). Similar conclusions are made by OECD (2022) that the limitation of the market concentration not only improves efficiency but also increases equality. This supports the claim by Stiglitz (2015) that the market power that is unregulated results in the extraction of rents, political capture, and increased inequality.

Literature has also changed in terms of its methodology. Linear frameworks have been replaced by nonlinear, information-theoretic models that are better positioned to model complex, asymmetric dependencies. In early econometric studies, causality was largely based on the Granger (1969) causality test, which determined whether variation in one time series could gain more predictive power in another. As much as they are common, the traditional Granger and panel-Granger causality tests are based on linearity and homogeneity across cross-sectional units. Thus, they are not reliable in real-world macroeconomic data where structural breaks, heterogeneity, and nonlinearity dominate (Holtz-Eakin et al., 1988; Dumitrescu & Hurlin, 2012). These classical models are not very effective when causal relationships are nonlinear or dependence is in a higher-order form, like conditional variance. Besides, they ignore the dynamics of qualities and symbolic dependencies, which tend to define social and institutional processes.

In order to overcome these shortcomings, entropy-based causality information theoretic frameworks have become eminent. Measures of entropy characterize uncertainty and information flow between variables, which makes it possible to identify a causal impact in variables that are not necessarily linearly related. In this paradigm, Transfer Entropy (TE), suggested by Schreiber (2000), quantifies the decrease in the uncertainty of one process under the past of another, where non-parametric, model-free measures of directional dependence are given. More recent approaches like Symbolic Transfer Entropy (STE) build on this idea by converting time-series data into symbolic representations of time-series, which are resistant to noise, non-normality, and structural variation and maintain ordinal relationships (Matilla-García et al., 2014). The symbolic approach is especially efficient in the case of economic data that have heterogeneous distributions or qualitative characteristics. STE allows causality analysis in longitudinal or pooled contexts, where both space and time are important, by adding symbolized histories of units, and testing whether lagged effects of one variable make the entropy of a second variable smaller conditional on its own history (Dumitrescu & Hurlin, 2012; Matilla-García et al., 2014).

The innovation of the methodology of STE is that it is designed as non-parametric and with few assumptions. The fact that it represents each series in a discrete ordinal pattern avoids the linearity requirement that cripples conventional panel causality tests. Monte Carlo experiments prove that symbolic methods preserve appropriate size and greater power even in situations where data are heterogeneous, contain outliers, or structural break-even parametric Granger tests lose their validity (Matilla-García et al., 2014). In addition, directional causality, i.e., whether information is mostly directed by a variable *X* to variable *Y* and/or the other way around, can be determined using the concept of net transfer entropy. This is particularly relevant in the multivariate scenarios of macro-finance, where the feedback is asymmetric. The pooled STE method, therefore, offers a strong causality test of heterogeneous units, which combines the benefits of longitudinal data with information theory flexibility. Bootstrapping procedures are typically used to establish significance levels and ensure statistical rigor under minimal distributional assumptions.

The applicability of STE to the inequality-corruption-market power model is high. Economic interdependencies between these variables are nonlinear, asymmetric, and path-dependent. These are exactly the situations where entropy-based approaches flourish. Linear models can only represent short-run correlations, but not whether, as an example, changes in market power pass information to changes in corruption, or vice versa. Entropy-based causality reveals such flows of information without any form of restrictive parameters. The STE is capable of uncovering the subtle yet consistent causal relationships in OECD settings where the institutions are fairly constant, and yet the heterogeneity in the economies is seen. As an illustration, Net-TE would indicate a positive relationship between market power and corruption, and vice versa. The existence of a strong Net-TE would indicate the mediating position of corruption in the redistribution process. With such quantification of these directed flows of information, STE can bridge the gap in methodology between theory and empirics, providing a single framework to model the causality of uncertainty.

To the best of our knowledge, the application of Symbolic Transfer Entropy to the specific triadic relationship among income inequality, corruption, and market power remains novel. While STE has previously been applied to financial time series (Matilla-García et al., 2014), energy markets (Duan et al., 2013), and macroeconomic volatility transmission (Camacho, Romeu & Ruiz-Marin, 2021), its application within the domain of institutional economics and distributional analysisremains limited. Existing information-theoretic studies on inequality have largely relied on bivariate transfer entropy or mutual information approaches, rather than the pooled longitudinal STE framework adopted here in this study. Similarly, although corruption has been examined using entropy-based complexity measures, prior studies have not incorporated market power as a third structural domention. The present study addresses this methodological gap by being, to the best of our knowledge, the first to apply the pooled STE-Net-TE framework to the inequality-corruption-market power nexus in a longitudinal OECD setting.

Overall, the growing body of literature acknowledges that income inequality, corruption, and market power are a highly coupled system. The dynamics of income inequality and corruption should be understood through methodological instruments that can be applied to capture nonlinear feedback and the cross-sectional heterogeneity of this system. Such complex macro-institutional interactions cannot be well analyzed with the help of traditional linear Granger causality approaches, though they are foundational. The use of information-theoretic methods, in particular, Symbolic Transfer Entropy, is one of the important steps forward, as it allows identifying the latent causal dynamics that are contained in the joint dynamics of economic and governance variables.

3. Research methodology

3.1. Data and preprocessing

Using a nonlinear information-theoretic framework, this paper investigates the causality relationship between income inequality, corruption, and market power among the OECD nations in the 1984–2024 period. The methodology combines the longitudinal symbolic analysis and pooled Symbolic Transfer Entropy (STE) estimation to identify the enigmatic and asymmetric information pathways between economic variables. The approach is based on the Symbolic Transfer Entropy (STE) model created by Camacho et al. (2021), which is a modification of the initial viewpoint of transfer entropy presented by Schreiber (2000) to the problem of longitudinal data. This approach departs from conventional econometric techniques, which in most cases are based on linear autoregressive models and are highly distributional. On the contrary, the directional flow of information between time series is captured by STE in a non-parametric fashion, which gives it resistance to nonlinearity, non-stationarity, and cross-country heterogeneity (et al., 2021).

The annual data of 38 OECD countries were used to perform empirical analysis. All-time series were initially differenced and standardized in order to eliminate the effects of scale and reduce non-stationarity. There were three macro-structural measures used to reflect the constructs in the study, namely the Gini coefficient of income inequality, the Bayesian Corruption Index (BCI) of corruption, and the trade union density (inverted) as a measurement of market power. These variables, contribute to the multidimensional interaction of the redistributive outcomes, institutional governance, and economic concentration in the OECD economies.

The Gini coefficient, or Gini index, as a measure of income inequality, was calculated based on the Standardized World Income Inequality Database (SWIID) version 9.9 (Solt, 2020). The Gini coefficient quantifies the deviation of actual income distribution from perfect equality, taking values between 0 (complete equality) and 1 (complete inequality). The usual Gini values in the OECD countries lie between 0.2 and 0.4. The SWIID offers cross-nationally comparable net and gross income inequality estimates since 1960 up to date, maximizing both temporal and spatial coverage, in comparison to other data sets, i.e., the Luxembourg Income Study (LIS) and Deininger-Squire dataset. This paper uses net Gini indices, which measure inequality in disposable household income after taxes and transfers. The methodological advantage of SWIID is that it uses a multiple imputation technique, which reduces measurement error and enhances comparability among nations (Solt, 2020).

The Bayesian Corruption Index (BCI) created by Standaert (2015) was used to measure corruption. The BCI is an improvement of previous data, including the Corruption Perception Index (CPI) by Transparency International and Worldwide Governance Indicators (WGI) by the World Bank. It uses a Bayesian Gibbs sampler to add together several corruption indices whilst considering the time dependence and measurement error. It yields more reliable estimates and confidence ranges and bypasses the issues of selection bias and volatility that characterize perception-based indices (Standaert, 2015). The BCI is measured in the range of 0 through 100, with a higher point signifying a higher corruption-perceived state. The Bayesian construction of it guarantees that such a slight variation of underlying indicators does not create artificial variation of rankings. Hence, it is especially appropriate when long-run cross-country analysis is required.

The third component was market power and was proxied by the inverted trade union density, which was adopted from OECD Labour Force Statistics 2024 Trade Union Edition 2024. Trade union density is used to indicate the membership of wage and salary earners within a union to the total number of workers. It represents the bargaining power of labor as compared to the employers. Based on the conceptualization of Piketty (2014), a fall in unionization is also in line with the increased market power of the employer. Therefore, an inverse indicator of competition in the labor market. This negative correlation, in which decreasing membership is an indicator of increasing employer market power, is captured by the inverted union membership indicator employed in this study. This choice of the proxy corresponds with the general literature of decreasing union density with rising inequality and firm concentration (De Loecker, Eeckhout & Unger, 2020).

The three series of income inequality, corruption, and market power were merged into a balanced panel covering 1984 to 2024. The dataset thus captures both structural and institutional evolution in OECD economies across four decades. Before analysis, all variables were transformed into standardized z-scores and tested for structural breaks using the Zivot–Andrews unit root test to ensure that symbolization was not distorted by extreme discontinuities. For robustness purposes, we also employ the World Bank Gini Index and the Worldwide Governance Indicators Control of Corruption estimate as alternative measures (see Section 4.5).

3.2. *Causality for pooled data*

3.2.1. *Linear approaches*

Consider two real-valued stationary time series, $\{y_{i,t}\}_{t\in I_i}$ and $\{x_{i,t}\}_{t\in I_i}$ where the time index t belongs to the set $I_i = \{1,\cdots,T_i\}$ of cardinality T_i, and each cross-sectional unit is denoted by $i = 1,\cdots,N$. A traditional approach for testing causal relationships in panel settings is based on estimating the following fixed-coefficient model with individual effects:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_{ik} y_{i,t-k} + \sum_{k=1}^{K} \beta_{ik} x_{i,t-k} + e_{i,t} \tag{1}$$

where the error terms $e_{i,t}$ are independently and normally distributed with a mean of zero and a variance σ_i^2.

Although the literature on panel Granger causality is extensive, two influential contributions stand out. The first is the work of Holtz-Eakin et al. (1988), who assume that heterogeneity across units arises only from individual fixed effects α_i. Under this assumption, the autoregressive and causal coefficients are homogeneous across units, that is, $\gamma_{ik} = \gamma_k$ and $\beta_{ik} = \beta_k$. The model is estimated using instrumental variables applied to quasi-differenced equations to address endogeneity concerns. Testing for causality in this framework consists of evaluating the joint null hypothesis $\beta_k = 0$ for all $k = 1,2,\cdots,K$. Rejection implies that causality exists for all individuals in the panel. The test statistics are obtained by comparing the restricted and unrestricted residual sums of squares, yielding an asymptotic chi-square distribution.

A second, less rigid contribution is given by Dumitrescu and Hurlin (2012). Their framework allows the coefficients to differ across cross-sectional units, permits varying lag structures, accommodates unbalanced panels, and accounts for cross-sectional dependence. In the null hypothesis of noncausality, all causal coefficients take the value of $\beta_{ik} = 0$ for all $k = 1, 2, \cdots, K$ and $i = 1, 2,\cdots,n_1$. Under the alternative hypothesis, at least one unit exhibits causality, meaning that $\beta_{k_0} \neq 0$, for all $i = N_1 + 1, \cdots, N$, with $N_1 \in [0, N-1])$. The procedure requires estimating N individual regressions and computing the Wald statistic W_i for each cross-sectional unit. The panel test statistic is then defined as the simple average:

$$W = \frac{1}{N}\sum_{i=1}^{N} W_i \tag{2}$$

Assuming that the statistics W_i are independent and identically distributed across units, Dumitrescu and Hurlin (2012) show that the standardized form of this average converges to a standard normal distribution:

$$Z = \sqrt{\frac{N}{2K}}(W - K) \rightarrow N(0,1) \tag{3}$$

When both the time dimension and cross-section dimension are fixed, they recommend using the mean Wald statistic in equation (2) and deriving critical values through stochastic simulations. In the presence of cross-sectional dependence, they also propose bootstrap procedures to correct for distortions in finite samples.

Finally, it is worth noting that while transfer entropy originates from information theory, Barnett et al. (2009) show that transfer entropy and linear Granger causality coincide for stationary Gaussian processes. Transfer entropy provides an equivalent to linear causality tests, underscoring the fact that the former is more generalized and takes place in a wider and possibly nonlinear setup.

3.2.2. Symbolic analysis

The idea of symbolic dynamics is simple. The phase space of a system is divided into a finite set of regions, and each of them is marked by a distinct symbol belonging to a set of symbols, which is predefined by an alphabet. Instead of the direct numerical path of the system, the analysis is done on the sequence of symbols visited as the system moves forward in time. These symbolic sequences, however, are enough to describe the key properties of the dynamical character of the system as shown by Collet and Eckmann (2009).

Ordinal patterns are the symbolic representation that we are assuming in this study since they simply presuppose that the underlying data is ordered, and thus are especially appropriate in economic time series. To standardize the notation, we write $\{y_{i,t}\}$ and $\{x_{i,t}\}$ two sets of time series that have real values. Each series is embedded into an m-dimensional vector that represents local time information: m is the embedding dimension ($m \geq 2$).

$$x_{im}(t) = (x_{i,t}, x_{i,t+1}, \cdots, x_{i,t+m-1}) \tag{4}$$

$$y_{im}(t) = (y_{i,t}, y_{i,t+1}, \cdots, y_{i,t+m-1}) \tag{5}$$

These m-dimensional histories provide a summary of the short-run behaviour of each series, in terms of how it behaves across m consecutive time points. The m-histories available in a series of lengths T_i are $T_i^* = T_i - m + 1$. Aggregating across all N cross-sectional units yield a total of $T^* = T_1^* + \cdots + T_N^*$ embedded vectors for the analysis.

To make the symbolic representation formal, we will adopt the notation S_m to refer to the symmetric group of order $m!$, which is comprised of all possible permutations of length m. Each element $s = (s_1, s_2, \cdots, s_m)$ in S_m is referred to as a symbol, where each $s_j \in \{0, 1, \cdots, m-1\}$ and $s_j \neq s_h$ for all $j \neq h$. A time-series representation for the time series $\{y_{i,t}\}$, is symbolized by mapping each m-dimensional history $\{y_{im}(t)\}_{t \leq T_i^*}$ to a unique symbol $s \in S_m$ such that the following ordering conditions are realized:

$$y_{i,t+s_1} \leq y_{i,t+s_2} \leq \cdots \leq y_{i,t+s_m} \tag{6}$$

$$s_{j-1} < s_j \text{if} y_{i,t+s_{j-1}} = y_{i,t+s_j} \tag{7}$$

A history $y_{im}(t)$ that satisfies these conditions is of the s-type. The former condition gives the ordinal arrangement with which the embedding structure is characterized, and the latter makes the symbol unique by placing tied values in order. This tie-break property does not matter in the case of continuous-valued time series, where equality is probability zero. This is the same process in trying to symbolize the series, $\{x_{i,t}\}$.

This mapping transforms the sequences of embedded vectors $\{y_{im}(t)\}_{t \leq T_i^*}$ and $\{x_{im}(t)\}_{t \leq T_i^*}$ into the sequence of ordinal patterns, which are denoted by $\{\xi_{im}^y(t)\}_{t \leq T_i^*}$ and $\{\xi_{im}^x(t)\}_{t \leq T_i^*}$, respectively. Each embedded history is linked to a specific symbolic label reflecting its inner structuring of order. With the symbolized sequences and an embedding dimension m, the probability of any symbol $s \in S_m$ is calculated as its empirical relative frequency in the respective symbolic sequence. Indicatively, the likelihood that the series $\{y_{i,t}\}$ produces the symbol s is:

$$p_{im}^y(s) = \frac{\#\{t = 1, \cdots, T_i^* | y_{im}(t) is of s - type\}}{T_i^*} \tag{8}$$

in which $\#\{\cdot\}$ refers to the cardinality of the set.

Following Matilla-García (2007) and Matilla-García and Marín (2008), the permutation entropy of the series $\{y_{i,t}\}$ is given as the Shannon entropy (Shannon, 1948) of the distribution of the $m!$ possible symbols:

$$h_m(y_{i,t}) = -\sum_{s \in S_m} p_{im}^y(s) \ln(p_{im}^y(s)) \tag{9}$$

The measure of entropy has been used to determine the degree of disorder or unpredictability of the symbolic sequence and is used to calculate symbolic transfer entropy.

The natural and intuitive interpretation of this measure of entropy exists. The m-history of a time-series each has some information, and the expected value of this information is the Shannon entropy, which is a measure of the uncertainty or unpredictability of the time series. Construction Permutation entropy is always non-negative and, in the range, $0 \leq h_m(y_{i,t}) \leq ln(m!)$.

The lower bound is attained when the series can be described using only a strictly monotonic (increasing or decreasing) pattern, when it can be coded by only one ordinal pattern. On the other hand, the upper bound can be related to an entirely random process where every $m!$ symbol has an equal likelihood of occurrence.

The symbolization framework needs to be expanded to a multivariate framework to analyze the causal relationship among variables. To make this clearer, we shall confine ourselves to the two-dimensional case, but the identical reasoning can be applied to any time series of any n dimensions. An example of a cross-sectional unit is a bivariate process $\left\{y_{i,t}, x_{i,t}\right\}_{t\in I_i}$. Each of the series is then fixedly embedded in its own sequence of m-histories, to create the vectors $\{y_{im}(t), x_{im}(t)\}_{t\leq T_i^*}$. These embedded representations provide the basis for constructing joint ordinal patterns that summarize the local dynamic evolution of the two variables.

In order to generalize the symbolic environment to the bivariate case, we define the symbol space $S_m^2 = S_m \times S_m$, the direct product of two copies of the symmetric group S_m. Each element of this space is denoted $s_{yx} = (s_y, s_x)$, where s_y and s_x are the ordinal patterns associated with the series y and x, respectively. A pair of m-histories $\{\{y_{im}(t), x_{im}(t)\}$ is said to be of type s_{yx} if $y_{im}(t)$ corresponds to s_y-type and $x_{im}(t)$ corresponds to a symbol s_x-type. This generates a bivariate symbolic sequence $\{\xi_{im}^{y}(t)\}$.

The probability of any joint symbol $s_{yx}\in S_m^2$ is the relative frequency, which is determined empirically.

$$p_{im}^{yx}(s_{yx}) = \frac{\#\{t = 1, \cdots, T_i^* | (y_{im}(t), x_{im}(t)) is of s_{yx} - type\}}{T_i^*} \tag{10}$$

According to these probabilities, the Shannon permutation entropy of the joint process of $\left\{y_{i,t}, x_{i,t}\right\}$ is defined as:

$$h_m(y_{it}, x_{it}) = -\sum_{s_{yx}\in S_m^2} p_{im}^{yx}(s_{yx}) \ln(p_{im}^{yx}(s_{yx})) \tag{11}$$

This entropy quantifies the total amount of information or degree of uncertainty contained in the combined dynamics of both time series. A key tool for studying causal relationships is the conditional permutation entropy, which measures the uncertainty of $\left\{y_{i,t}\right\}$ when the information contained in $\{x_{i,t}\}$ is taken into account. By definition, it is obtained by averaging the uncertainty of y over all possible realizations of x. The conditional entropy satisfies the standard chain rule:

$$h_m\left(y_{i,t}|x_{i,t}\right) = h_m\left(y_{i,t}, x_{i,t}\right) - h_m(x_{i,t}) \tag{12}$$

This quantity equals zero when the evolution of y is completely determined by x, and it coincides with the unconditional entropy of y when the two series are independent. The generalization of this approach to compute any other conditional entropy follows directly from the same principles.

3.2.3. A transfer entropy test for panel data

Extending causality testing to longitudinal (panel) data requires combining information across all cross-sectional units. A direct way to do this is to stack the raw time-series observations from each unit on top of one another. For example, assessing whether lagged values of x (delayed by r periods) help predict current values of y, or vice versa, would involve constructing pooled vectors such as:

$$\begin{aligned}
\{y_t\} &= \left\{y_{1,r}, \cdots, y_{1,T_i}, \cdots, y_{N,r}, \cdots, y_{N,T_i}\right\}, \\
\{x_t\} &= \{x_{1,r}, \cdots, x_{1,T_i}, \cdots, x_{N,r}, \cdots, x_{N,T_i}\}, \\
\{y_{t-r}\} &= \left\{1, \cdots, y_{1,T_i-r}, \cdots, y_{N,1}, \cdots, y_{N,T_i-r}\right\}, \\
\{x_{t-r}\} &= \{1, \cdots, x_{1,T_i-r}, \cdots, x_{N,1}, \cdots, x_{N,T_i-r}\},
\end{aligned} \tag{13}$$

However, conducting block exogeneity tests using these stacked observations imposes the restrictive assumption that all cross-sectional units share an identical dynamic relationship between x and y. This assumption is unrealistic in most empirical settings. For this reason, Holtz-Eakin et al. (1988) introduced fixed effects to account for heterogeneity, while Dumitrescu and Hurlin (2012) allowed for heterogeneous panel structures and varying lag orders.

Instead of pooling raw observations, the present approach following Camacho, Romeu & Ruiz-Marin (2021), proposes pooling the symbolic representations of the time series. That is, each cross-sectional unit is first transformed into its sequence of ordinal patterns, and then these symbols are stacked across units. Transfer entropy is then computed from the pooled symbols of $\{x_{t-r}\}$ to the pooled conditional entropy $h_m(y_t|y_{t-r}, x_{t-r})$. It involves the manipulation of sequences of pooled symbols instead of pooled numeric values.

For this method to be valid, the symbolization procedure must produce comparable ordinal patterns across all units, ensuring that the symbolic alphabet is consistent. Once symbolization is performed, the pooled conditional entropy can be computed by summing the conditional entropies across the N units:

$$h_m(y_t|y_{t-r}, x_{i,t}) = \sum_{i=1}^{N} h_m\left(y_{i,t}|y_{i,t-r}, x_{i,t-r}\right) \tag{14}$$

This conditional pooled entropy is a measure of the overall content of information received when the lagged values of x are included in the prediction of y in all cross-sectional units.

In order to come up with a causality test within this pooled symbolic environment, we use the Symbolic Transfer Entropy (STE) measure suggested by Schreiber (2000). STE is used to measure the additional information that is given by the history of x as predictive of y, given the history of y itself.

$$STE_{x\to y}(m, r) = h_m(y_t|y_{t-r}) - h_m(y_t|y_{t-r}, x_{t-r}) \tag{15}$$

A positive value of $STE_{x\to y}$ indicates that the lagged values of x contribute additional information beyond that contained in the lagged values of y, providing evidence of directional information flow from x to y.

This transfer entropy measure can be interpreted as the reduction in uncertainty about the current state of y_t obtained by incorporating information from both y_{t-r} and x_{t-r}. A large value of transfer entropy from x to y indicates that the lagged values of x contain predictive information about the evolution of y, whereas a small value suggests that y_t evolves independently of the past of x. As noted by Barnett et al. (2009), Hlaváčková-Schindler (2011), and Duan et al. (2013), transfer entropy therefore provides a natural, information-theoretic analogue of Granger causality. Under mild assumptions of stationarity and ergodicity, the estimator of transfer entropy is asymptotically unbiased. The probabilities of observing each symbol type estimated through expressions such as equations (8) and (10) can be seen as U-statistics. Accordingly, when the underlying time series are stationary and ergodic, the asymptotic unbiasedness result of Aaronson et al. (1996) applies. Paninski (2003) further shows that the bias of the Shannon entropy estimator is given by:

$$\frac{m!^h - 1}{2TN} + \mathcal{O}\left(\frac{1}{N^2T^2}\right) \tag{16}$$

where h denotes the number of variables. The dominant term in this expression vanishes as the product TN grows large for any fixed embedding dimension m. Under the null hypothesis of no causality from x to y, the population value of $STE_{x\to y}(m, r)$ equals zero. When causality is present, the true value is strictly positive. This distinction forms the basis of the proposed causality test for longitudinal data.

Deriving the exact or asymptotic sampling distribution of the test statistic $STE_{x\to y}(m, r)$. It is difficult because the dynamic evolution of the series can alter the distribution of symbols and, consequently, the distribution of entropy estimates. To overcome this challenge, a bootstrap method is used to estimate the null distribution. One important condition is that the bootstrap method maintains the null hypothesis of no causation of the resampled data. To achieve this, the time series $\{y_{i,t}\}$ and $\{x_{i,t}\}$ are resampled independently within each cross-sectional unit using the stationary bootstrap of Politis and White (2004). Thus, it maintains the serial dependence structure of each process.

The testing procedure begins by computing the observed value of the transfer entropy $STE_{x\to y}(m, r)$ from the original pooled sequences $\{y_t\}$ and $\{x_t\}$. For each bootstrap replication, new samples $\{x^b_{i,t}\}$ and $\{y^b_{i,t}\}$ are generated. These resampled series are then symbolized to obtain the sets of ordinal patterns $\{\zeta^{y_t y_r x_r}_{m,b}(t)\}$, $\{\zeta^{y_r x_r}_{m,b}(t)\}$, $\{\zeta^{y_t y_r}_{m,b}(t)\}$ and $\{\zeta^{y_r}_{m,b}(t)\}$. From these symbols, the relative frequencies are computed, and the corresponding conditional permutation entropies are obtained:

$$h^b_m(y_t|y_{t-r})\text{and}h^b_m(y_t|y_{t-r}, x_{t-r}) \tag{17}$$

These entropy estimates yield a bootstrap realization of the transfer entropy statistic,

$$STE^b_{x\to y}(m, r) = h^b_m(y_t|y_{t-r}) - h^b_m(y_t|y_{t-r}, x_{t-r}) \tag{18}$$

and repeating this procedure B times produces a collection of bootstrap statistics,

$$\left\{STE^b_{x\to y}(m, r)\right\}_{b=1}^{B} \tag{19}$$

The bootstrap p-value is then computed as follows:

$$P_b = \frac{1}{B}\sum_{b=1}^{B} I\left(STE^b_{x\to y}(m, r) > STE_{x\to y}(m, r)\right) \tag{20}$$

where $I(\bullet)$ is an indicator function equal to 1 when the condition is satisfied and 0 otherwise. The null hypothesis of no causality from x to y is rejected at the significance level α whenever $P_b < \alpha$. The reverse null hypothesis that y does not cause x is assessed by applying the same procedure to $STE_{x\to y}(m, r)$.

Another issue with causality analysis is that it is not only necessary to decide whether there is a causal relationship or not, but also how information flows. Caines et al. (1981) identified four potential causal configurations that could be used when analyzing the relationship between two time series, x and y. The former case is a unidirectional causality of x on y. It is true that in this case, the past of x gives predictive information about the development of y, but not the opposite. Formally, this requires that $STE_{y\rightarrow x}(m,r) = 0$ and $STE_{x\rightarrow y}(m,r) > 0$.

The second situation is the example of unidirectional causality between y and x, when the predictive content moves in a reverse direction. This is when $STE_{y\rightarrow x}(m,r) > 0$ and $STE_{x\rightarrow y}(m,r) = 0$. The third scenario comes when the two series are independent of each other, that is, neither of them carries information that can enhance the forecasting of the other. It is evident in the transfer entropy values of $STE_{y\rightarrow x}(m,r) = STE_{x\rightarrow y}(m,r) = 0$.

The last model is a two-way (or bidirectional) causality, where both series provide predictive information of the other. In this case, both values of transfer entropy are positive, i.e. $STE_{y\rightarrow x}(m,r) > 0$ and $STE_{x\rightarrow y}(m,r) > 0$, even though they may have the same magnitude.

where x and y have a bidirectional causal dependence, the issue of determining the direction of information flow that is predominant becomes relevant. To cope with this, the analysis has used Net Transfer Entropy (NTE), which is defined as:

$$NTE_{xy}(m,r) = STE_{y\rightarrow x}(m,r) - STE_{x\rightarrow y}(m,r) \tag{21}$$

This is an easy and intuitive measure of the direction of causal influence that exists. When $NTE_{xy}(m,r)$ is positive, it means that the amount of information that is passed between y and x is higher than the amount of information in the other direction, hence indicating a predominating causal relationship between y and x. On the other hand, the negative value shows that x has a greater directional impact. In the case where the net measure is zero, there are two cases. Either the series are independent, when both transfer entropy measures are also equal to zero, and are two-way causal with equal strength, which is shown by strictly positive but symmetric transfer entropy magnitudes.

Assessing the significance of the net direction of causality follows naturally from the bootstrap procedure used earlier. After computing the observed statistic $NTE_{xy}(m,r)$, the bootstrap resampling generates a distribution of B net transfer entropy statistics, denoted $NTE^{b}_{xy}(m,r)$. A two-tailed test of the null hypothesis $NTE_{xy}(m,r) = 0$ is then conducted by calculating the proportion of bootstrap realizations for which $|NTE^{b}_{xy}(m,r)| > |NTE_{xy}(m,r)|$. Similarly, a one-tailed test for the hypothesis that the net flow is directed from y to x evaluates the proportion of bootstrap values satisfying $NTE^{b}_{xy}(m,r) > NTE_{xy}(m,r)$. Rejecting this null indicates that the dominant causal direction runs from y to x. It is also the same case in determining dominance in the reverse direction.

All the unordered pairs which are INEQ ↔ CORR, CORR ↔ MP, and INEQ ↔ MP, at the pooled and country level, were computed as both STE and NTE. The pooled analysis is used to capture aggregate OECD-level directional information flows, whereas country-level estimation is available to make cross-national allowances in causal dynamics. The latter allows determining which countries are statistically significant in terms of transferring symbolic information, which is characteristic of localized structural or institutional mechanisms.

This methodological approach has a number of merits over traditional Granger-based causality models. To begin with, it does not require a linear functional specification, which enables it to identify asymmetric and nonlinear relationships. Second, the symbolization process is monotonic scale-invariant, so that it is resistant to any difference between the scale of measurements and outliers typical of macroeconomic variables. Third, the test has the power to pool longitudinal symbolic sequences and is still able to

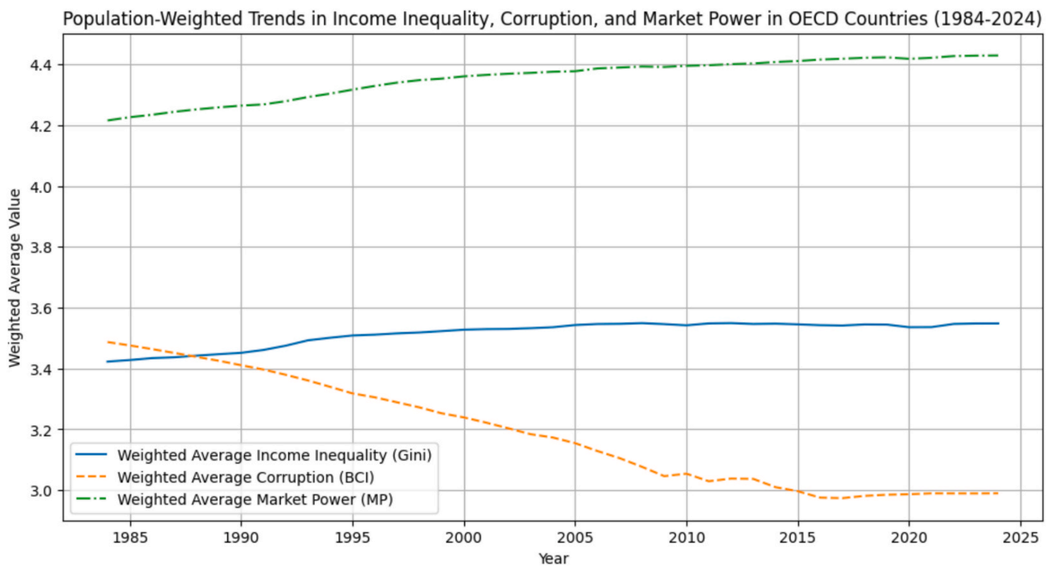

Fig. 1. Population-weighted trends in income inequality, corruption and market power.

accommodate cross-sectional heterogeneity. Together, these characteristics render the Symbolic Transfer Entropy technique an effective mechanism in the process of uncovering the multidirectional causality structure of inequality, corruption, and market power in the OECD economies.

4. Results and discussion

4.1. Overview and trend analysis

This section reports the empirically calculated pooled longitudinal Symbolic Transfer Entropy (STE) analysis output and the accrued Net Transfer Entropy (Net-TE) values of the tri-variable system of income inequality (INEQ), corruption (CORR), and market power (MP) in OECD countries between 1984 and 2024. The analysis uses the equal-frequency symbolic binning, calculates pooled conditional entropies, and employs the stationary bootstrap resampling statistical inference at the 5% significance level. The combination of the STE and Net-TE findings demonstrates the scale, the direction, and the value of the information flows between the three variables in the pooled and country-specific levels.

Fig. 1 reveals three important long-run patterns. First, income inequality rose consistently from the mid-1980s through the mid-2000s, driven by financial liberalisation, technological change favouring skilled labour, and declining collective bargaining institutions. Although the growth rate moderated post-2008, inequality remains structurally elevated across OECD economies. Second, corruption exhibits a secular downward trend, reflecting improvements in governance standards, anti-corruption reforms, and digitisation of public services. The marginal slowing of this decline in the 2010s suggests convergence toward institutional floors where further gains become incremental. Third, market power (inverted union density) shows a gradual upward trend through the 1990s and early 2000s, consistent with the erosion of labour bargaining power, before stabilising as employer concentration transitions toward monopsony strength and digital platform dominance. These trends collectively challenge the assumption that governance improvements automatically produce equitable outcomes. The simultaneous rise in inequality and decline in corruption suggests that efficiency gains from better governance may disproportionately accrue to high-income households when labour bargaining power is weak. Moreover, the divergence between market power and corruption trends indicates that market concentration in OECD economies increasingly operates through technological dominance and intellectual property regimes rather than traditional regulatory capture Naeem et al. (2025) and Ghouse et al. (2025). These patterns provide the empirical foundation for the STE analysis that follows, motivating our focus on nonlinear and asymmetric interdependencies that linear trend descriptions cannot adequately capture.

4.2. Pooled symbolic transfer entropy (STE)

Adding to the descriptive dynamics above, this section examines the dynamic interdependency of income inequality (INEQ), corruption (CORR), and market power (MP) using the pooled Symbolic Transfer Entropy (STE) model. In contrast to linear causality tests, STE has an advantage in capturing nonlinear and asymmetric information flows, which enables a better learning of how structural and institutional variables interact over time across the OECD economies. STE offers an information-theoretic metric of causality that is particularly appropriate to complex macro-institutional dynamics by putting emphasis on uncertainty reductions between the past and present states of each pair of variables.

The pooled STE matrix indicating the average information transfer between the three variables in a directional form is shown in

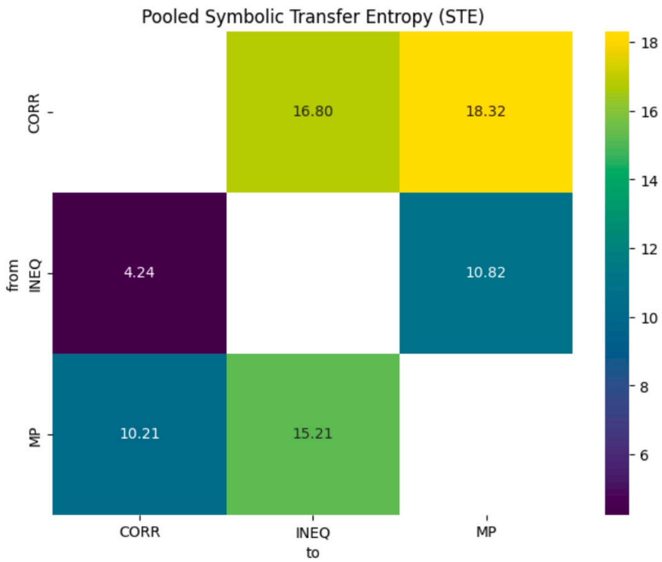

Fig. 2. Pooled Directed Symbolic Transfer Entropy (1984–2024).

Fig. 2. The heatmap shows an enormous asymmetry in the cause structure of the system. Corruption is the most prevalent source of the strongest flows, CORR → MP (18.32) and CORR → INEQ (16.80), showing the greatest STE magnitudes. These values suggest that historical trends in corruption have a lot of predictive value with respect to the change in market power and income inequality in the future. This is, in principle, aligned with the idea that corruption undermines competitive conditions, enables rentier behavior, and deteriorates institutional performance. Either of which can only serve to strengthen economic concentration and distributional inequalities. Incorporating even relatively sophisticated systems of governance in the OECD, even minor changes in corruption can be used to significantly alter policy execution, procurement, or regulatory enforcement. Thus, it can propagate quantifiable information effects to structural and distributive results.

Conversely, causal directions of income inequality to corruption (INEQ → CORR = 4.24) and income inequality to market power (INEQ → MP = 10.82) are much lower. These findings are indicative of the fact that income inequality changes do not have a high short-run predictive power on institutional or structural processes at the pooled level. Though theoretical research suggests that high inequality can undermine the quality of the institutions or make them vulnerable to political capture, these processes are long-term and are not likely to be reflected in high informational flow in annual data. The relatively higher value of INEQ → MP, but the comparative value of INEQ lies within the possible indirect effects of lower union bargaining power or decadent labour share, which can insidiously connect the growing inequality to rising employer concentration.

Market power itself is moderately influential on both income inequality and corruption, with the MP → INEQ (15.21) and MP → CORR (10.21) indicating a mid-range STE value. These findings are consistent with hypotheses that maintain that concentrated markets reduce wage competitiveness, mobility, and expand the capacity of firms to affect regulatory outcomes. However, the scale of these flows is subordinate to the ones due to corruption, which once again supports the point of corruption being a dominating factor in the dynamic system, and that it holds an upstream position.

In general, Fig. 2 demonstrates apparent causal asymmetry. Corruption serves as the most persuasive means of transferring information in a tri-variable relationship, and income inequality is very reactive. Nevertheless, it is the combination of the values of the STE that does not necessarily provide the direction prevailing in each pair of variables. That is why the following Net Transfer Entropy (Net-TE) analysis represents a more sophisticated measure of the net causal balance that allows for a clearer evaluation of the directional dominance and determines the general causal hierarchy between corruption, market power, and income inequality.

4.3. Pooled Net Transfer Entropy (Net-TE)

Whereas the pooled STE matrix can give the magnitude of directional information flows, it is not able to indicate which direction prevails with each pair of variables. To solve this, the Net Transfer Entropy (Net-TE) metric is used to assess a change in opposite flows of STEs, enabling one to determine a dominant direction of causality. The Net-TE values are reported in Table 1 with stationary bootstrap p-values, and the relative strength and significance of these dominant causal channels are graphically shown in Figs. 3 and 4.

There are two statistically significant and directionally robust relationships that are pointed out in Fig. 3. Firstly, the INEQ ↔ CORR pair shows a highly positive value of the Net-TE (12.56) with statistical significance. This shows that the informational flow of corruption on income inequality is statistically more substantial than vice versa. This substantiates the previous findings of STE, where corruption continues to be a dominant cause of distributive results in the OECD economies. The size of the Net-TE indicates that this channel is not just of a contemporary nature but indicates a systematic upstream effect of institutional distortions in distributing income.

Second, the Net-TE of the CORR ↔ MP pair has a substantial negative value (−8.11), which suggests that the causal direction of the predominant relationship is downstream, i.e., market power to corruption. This imbalance is visually supported by Fig. 3, which presents a large bar at the bottom of it and the marker of significance. Structurally, it means that the growth of market concentration or employer power is more likely to cause deterioration of corruption relations rather than the opposite. This trend has been in line with other theories that concentrated economic power increases the capacity of firms to control their regulatory settings, receive special treatment, or have less accountability in institutional systems. Such mechanisms can be achieved in OECD by lobbying, regulatory capture, informational asymmetries, and barriers to entry, which are specific to a sector. The negative Net-TE therefore limits a negative feedback loop of governance in that economic dominance facilitates institutional erosion, which consequently underlies long-run governance.

These findings are also presented in Fig. 4 in a causal network diagram with the two important directed edges (MP → CORR and CORR → INEQ). The fact that the dominant direction between INEQ and MP is not statistically significant (Net-TE = 4.39; p = 0.083) indicates that, despite the relationship between income inequality, on the one hand, and market power, on the other, market power does not necessarily dominate over the former across the OECD countries. Such an absence of consistent directional considerations can imply heterogeneity among the member states. There are economies where inequality-motivated wage repression strengthens market strength, and others where there is market concentration, which contributes to wage dispersion. After the longitudinal pooling of the

Table 1
Pooled net transfer entropy.

Variable Pair	Net-TE	p-value	Dominant Direction
INEQ – CORR	12.556	0.000	CORR → INEQ
CORR – MP	−8.111	0.000	MP → CORR
INEQ – MP	4.387	0.083	No dominant direction

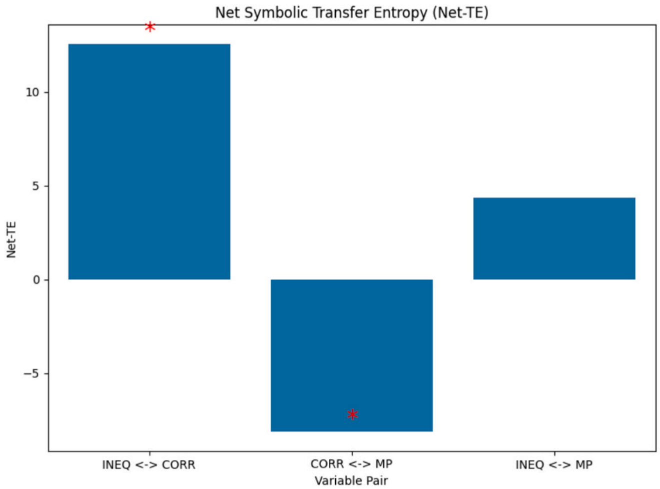

Fig. 3. Pooled Net Transfer Entropy.

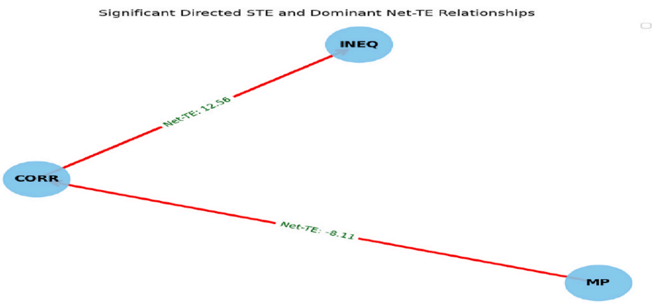

Fig. 4. Pooled Causal Network of Net-TE Dominance.

data, these divergent patterns cancel each other out to give an insignificant Net-TE result.

Taken together, the Net-TE outcomes of the pooled results demonstrate the presence of a logical and hierarchical cause-and-effect relationship: Market Power → Corruption → Income Inequality.

This channel emphasizes the stratum of institutional and structural factors of inequality. The market concentration seems to generate situations that produce distortions in the process of governance and later dictate the distributive outcomes. The results suggest that in OECD countries, income inequality appears to be influenced not only by labour-market and technological factors, but is mediated by institutional quality, in particular, the corruption dynamics based on market power. The findings suggest the importance of coordinated reforms where imposing tougher antitrust laws can indirectly alleviate corruption pressures, and anti-corruption tools can be used to play the primary role in eliminating long-term inequality.

To conclude, the Net-TE analysis complements the previous STE findings by making the prevalent directions of the causal transmission clear. It shows that corruption is not an isolated phenomenon, and it is frequently preceded by a change in market power structure. On the other hand, corruption itself becomes a strong mediator of determining income inequality in developed economies. This multi-causal chain of events underlies a multi-dimensional concept of income inequality by confirming the need to have joint governance-competition policy forms.

4.4. Country-level causality patterns

Although the general causes indicated by the pooled Net-TE group show a prevailing OECD-wide cause and effect pattern, Market Power → Corruption → Income Inequality, country-specific estimates define the existence of significant heterogeneity among national systems. All significant causal relations ($p < 0.05$) are summarized in Table 2, and the countries are ordered by the absolute size of their Net-TE in Fig. 5. Thus, it is possible to distinguish which economies have relatively high directional effects (see Table 2).

One of the observations made in Fig. 5 is that several European high-income countries, such as France, the Netherlands, Estonia, Ireland, and Hungary, stand at the top of the chart in the CORR → INEQ pair. These nations have high and statistically significant Net-TE values, which implies that the variations in corruption are a strong predictor of the changes in income inequality. Even relatively low levels of corruption can have outsized distributive consequences in social market economies where the state plays a substantial role in redistribution. In these nations, therefore, corruption is not only one of the institutional failures but a structural determinant of

Table 2
Significant country-level causal relations ($p < 0.05$).

Country	Dominant Direction	Pair	Statistic	p-value	Type
France	CORR → INEQ	INEQ–CORR	1.235	0.000	Net-TE
Netherlands	CORR → INEQ	INEQ–CORR	1.129	0.000	Net-TE
Estonia	CORR → INEQ	INEQ–CORR	1.084	0.020	Net-TE
Ireland	CORR → INEQ	INEQ–CORR	0.898	0.007	Net-TE
New Zealand	CORR → INEQ	INEQ–CORR	0.819	0.007	Net-TE
Spain	MP → INEQ	INEQ–MP	0.978	0.030	STE
Costa Rica	MP → CORR	CORR–MP	−1.359	0.000	Net-TE
Greece	MP → INEQ	INEQ–MP	0.970	0.010	Net-TE
Poland	MP → CORR	CORR–MP	−0.905	0.017	Net-TE
Belgium	MP → CORR	CORR–MP	−0.771	0.030	Net-TE
Hungary	CORR → INEQ	INEQ–CORR	0.655	0.040	Net-TE
France	CORR → INEQ	INEQ–CORR	1.048	0.010	STE
Spain	MP → INEQ	INEQ–MP	0.978	0.030	STE

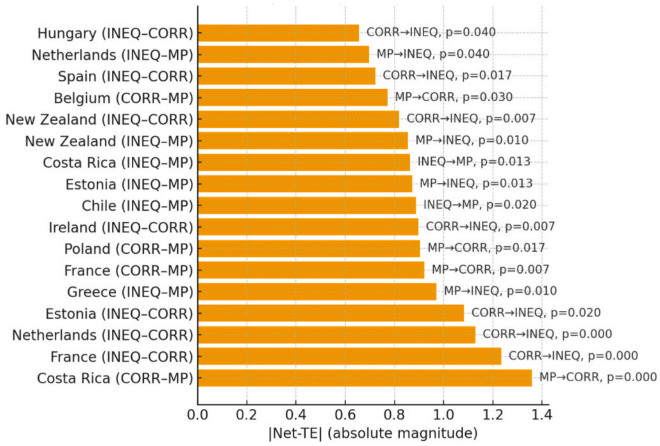

Fig. 5. Countries with Significant Net-TE ($p < 0.05$).

inequality.

The second category of countries, such as Spain, Greece, and Chile, exhibits strong MP direct effects on INEQ, implying that market concentration has a direct effect on income distribution that is not mediated by the corruption process. Such countries have gone through a significant upheaval in the labour market institutions, a wave of privatization, and consolidation of sectors in the past decades. The large STE and Net-TE flows suggest that the existence of strong companies and monopolistic labour market conditions enhances the expansion of income inequalities. It is important to note that Spain is referred to twice in the list of significant results, and this fact supports a high predictive value of market power in the creation of inequality within the country.

The third pattern is observed in countries like Costa Rica, Poland, and Belgium, in which MP → CORR is significant and negative. This means that market concentration increases before corruption increases, and this is expected by the theory of strong firms being known to impact/weaken regulatory settings. In smaller or more concentrated economies, disproportionate lobbying ability, regulatory capture, or informal influence on political decision-making may be due to high market power. For these countries, the results reveal a governance vulnerability pathway where structural concentration is associated with weakening institutional quality. This may subsequently affect distributive outcomes.

Lastly, countries like New Zealand and Estonia have significant but smaller-scale effects of CORR on INEQ. These cases hint at a similar dynamic to continental Europe but with more moderate institutional and distributive sensitivities. Their lower Net-TE numbers might be due to more effective institution protection or less effective public sector institutions that filter the corruption to the inequality channel.

Taken together, these heterogeneous results reinforce the robustness of the pooled causal mechanism while revealing meaningful national variation in how institutional and structural drivers interact. The European core economies highlight corruption as a primary mediator of distributive change, whereas Southern European and Latin American cases emphasize the structural roots of governance distortions via market concentration. Smaller OECD members show moderated versions of the same pathways, reflecting differences in institutional capacity, regulatory density, and economic composition.

This national-level breakdown, hence, reinforces the interpretation of the combined findings. Even though the causal relationship Market Power → Corruption → Income Inequality is true on average, its specific strength and exact form is contingent on the national institutional format and market organization. These results highlight the need for policy interventions to be context-dependent. Thus, competition policy can be enhanced with the most benefit in countries where MP → CORR is highest, and anti-corruption reforms can bring the greatest distributive benefits where CORR → INEQ is the strongest.

4.5. Robustness check with alternative inequality and corruption measures

To ensure that our findings are not artefactual to the choice of measurement instruments, we conduct a robustness check employing alternative indicators for both income inequality and corruption (see Table 3). While the baseline analysis relies on the Standardized World Income Inequality Database (SWIID) and the Bayesian Corruption Index (BCI), this section substitutes the World Bank Gini Index (indicator: SI.POV.GINI) and the Worldwide Governance Indicators (WGI) Control of Corruption estimate (indicator: CC.EST), respectively. The WGI Control of Corruption is one of the most widely recognised governance indicators in the economics literature and captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption as well as state capture by elites and private interests (Kaufmann, Kraay & Mastruzzi, 2011).

The data constraints of the alternative measures reduce the sample to 37 OECD countries over the period 1996–2023. For market power, we employ the inverted self-employment rate (World Bank indicator: SL.EMP.SELF.ZS) as a proxy for the erosion of formal labour market protections and the consequent rise in employer bargaining power. While imperfect, this proxy is conceptually aligned with the literature documenting the inverse relationship between union density and self-employment patterns in advanced economies (OECD, 2023).

The robustness analysis as shown in Table 3 confirms the core findings of the baseline model. First, the dominant direction between corruption and income inequality remains CORR → INEQ (Net-TE = 0.0481, $p = 0.026$), consistent with the baseline result (Net-TE = 12.556, $p = 0.000$). The directionality is fully preserved: historical variations in corruption carry greater predictive information about subsequent changes in income inequality than the reverse. Second, the market power to corruption channel maintains its directional pattern (MP → CORR: Net-TE = 0.0159), though individual bootstrap significance is not achieved in this specification, likely reflecting both the shorter time span (1996–2023 versus 1984–2024) and the alternative market power proxy. Third, the inequality-market power relationship remains directionally ambiguous in the pooled data, consistent with the baseline finding of no statistically significant directional dominance (Net-TE = 4.387, $p = 0.083$).

The directional consistency across both measurement specifications strengthens confidence in the causal hierarchy identified in this study: Market Power → Corruption → Income Inequality. These results suggest that the core causal structure linking competitive conditions, governance quality, and distributional outcomes in OECD economies is robust to the choice of inequality and corruption measurement instruments.

The shorter sample period (1996–2023 versus 1984–2024) reduces the statistical power of the bootstrap inference, particularly for the country-level analysis, where time series lengths are further constrained by first-differencing. The use of self-employment as a market power proxy, while conceptually defensible, does not capture the full range of mechanisms through which employer concentration operates. Future research employing the full OECD trade union density series would permit a more direct comparison with the baseline specification.

5. Concluding remarks

The pooled and country-level Symbolic Transfer Entropy (STE) and Net Transfer Entropy (Net-TE) analysis yielded empirical results. Thus, give a coherent and theoretically consistent understanding of the dynamic relationship between market power, corruption, and income inequality in OECD countries. Across all levels of analysis, a hierarchical structure of information flows appears, whereby market power influences corruption and vice versa. On top of being empirically sound, this sequential ordering is also closely consistent with modern political-economy scholarship.

The findings of the STE and Net-TE indicate that corruption is the most prevalent information transmitter to income inequality, which supports the long-standing theoretical claims that corruption can function as a regressive institutional mechanism that involves redistribution of resources upwards and decreases institutional capacity to counter disparities (Gupta et al., 2002; Dincă & Strempel, 2025). Our finding of such a high CORR → INEQ flow is consistent with other empirical studies that found that corruption undermines tax progressivity, alters welfare distributions, and favors the groups already privileged with economic power (Keneck-Massil, Nomo-Beyala & Owoundi, 2021). Our results advance this literature by demonstrating that these effects are not merely correlational but directional and statistically significant even in high-income OECD contexts where corruption levels are generally low yet institutionally consequential.

Similarly, the existing MP → CORR dominance can be attributed to the theoretical and empirical evidence on the connection between market concentration and the decline of governance (Ades & Di Tella, 1999; Basihos, 2025). As indicated in the literature review, companies with high market power may possess greater capacity to influence political and regulatory processes, regulatory structure, or implementation regimes and convert economic dominance into institutional power (Troesken, 2007). The significant negative Net-TE from market power to corruption in the pooled results confirms that this mechanism is not an isolated phenomenon but a system-wide dynamic within OECD economies.

There is no common direction of causality between income inequality and market power at the level of the pooled data, which is

Table 3
Robustness check: net transfer entropy comparison.

Variable Pair	Baseline Net-TE	Baseline Dir.	Robust Net-TE	Robust Dir.
INEQ ↔ CORR	12.556***	CORR → INEQ	0.0481**	CORR → INEQ
CORR ↔ MP	−8.111***	MP → CORR	0.0159	MP → CORR
INEQ ↔ MP	4.387*	No dominant	0.0026	MP → INEQ (weak)

Note: Baseline uses SWIID Gini + BCI + inverted trade union density (1984–2024). Robustness uses World Bank Gini + WGI Control of Corruption + inverted self-employment rate (1996–2023). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ from stationary bootstrap with 500 replications.

also in line with the literature. As the works done by Autor et al. (2020) and De Loecker, Eeckhout & Unger (2020) demonstrate, an increase in market power is one of the factors that increase wage suppression and inequality, but the intensity of this mechanism differs significantly across countries and is frequently mediated by institutional factors like unionization, labour-market regulation, and welfare regime design (Cairó & Sim, 2024; 2018[1]; OECD, 2022). Meanwhile, the theories of reverse causation that income inequality undermines competition by facilitating elite influences postulate nonlinear and threshold effects (Policardo, Carrera & Risso, 2019). The fact that there is no directional dominance to be found in our pooled data that is stable is an indication that there is contextual dependency rather than contradiction.

Country-level heterogeneity reinforces this interpretation. The dynamics of CORR → INEQ are strong in Northern and Western European economies such as France, the Netherlands, Ireland, and Estonia, which aligns with the idea of the institutional model on the key role of the integrity of governance in determining the distributive outcomes of the advanced state of welfare. In the meantime, the flows of MP → INEQ or MP → CORR are strong in Spain, Greece, and Chile, which reflects the literature to document structural weaknesses, concentrated industrialization, and weaker regulatory systems. Such national trends reveal the mediating role of institutional settings on the causal chain that the pooled analysis has, and, therefore, supplement the larger theoretical argument that income inequality, corruption, and market concentration are components of an interlocking system and not independent variables.

The findings all indicate a multi-layered causal framework having important policy implications. To begin with, competition policy and antitrust enforcement can be used as upstream interventions that would help mitigate governance vulnerabilities through the accumulation of market rents. Second, corruption is a downstream distributive policy that has led to the significance of transparency, regulatory independence, and accountability when reducing income inequality. Third, because there is no common inequality-to-market-power causal direction, redistributive policy, in itself, will not be able to address structural concentration, where joint institutional and market reforms will have to be sought.

Given the causal hierarchy identified which is Market Power → Corruption → Income Inequality, our results suggest a clear sequencing priority for policy intervention. The first priority should be competition policy and antitrust enforcement, as market power represents the most upstream driver in the causal chain. By constraining economic concentration and reducing the capacity of dominant firms to capture institutional and regulatory processes, policymakers can address the root source of governance vulnerabilities. This upstream approach aligns with the theoretical prediction that market concentration generates the rents that subsequently sustain corrupt practices (Ades & Di Tella, 1999; Troesken, 2007). The second priority should be anti-corruption and transparency reforms. Since corruption functions as the critical structural mediator between market power and inequality, reducing institutionalised corruption through procurement transparency, lobbying regulation, revolving-door restrictions, and independent anti-corruption agencies can sever the transmission channel through which market concentration becomes distributional inequality. The third priority, income redistribution through progressive taxation and social transfers, remains important but should be understood as a downstream complementary measure rather than a standalone solution. Our finding of no consistent pooled directional dominance between inequality and market power suggests that redistributive policy alone cannot remedy structural concentration without simultaneous governance and competition reforms. In practical terms, this implies that integrated policy packages combining antitrust enforcement with transparency reforms are likely to yield more durable equitable outcomes than single-pronged interventions.

In addition, the application of STE and Net-TE, which was designed specifically to model nonlinear, asymmetric, and heterogeneous causal interactions, indicates that the conventional linear Granger-type models cannot be used to investigate complex institutional-economic systems (Holtz-Eakin et al., 1988; Dumitrescu & Hurlin, 2012; Matilla-García et al., 2014). The symbolic entropy approach shows concealed causal processes that would not have been visible in linear analyses. Hence, enhancing empirical insights into the rich nature of the deep structure of inequality and governance processes.

In conclusion, the study provides strong empirical support for a two-step causal mechanism linking market structure, governance quality, and income inequality in OECD countries. The results of the analysis show that market power has an upstream effect on corruption, and corruption, in turn, is a mediating factor that brings about changes in income inequality over four decades of data. Though the precise magnitudes of the different countries depend on institutional and structural factors, the causal hierarchy is generally consistent with the political-economy theories and recent empirical studies. This study fills this gap between theory and practice using pooled longitudinal Symbolic Transfer Entropy, which is a technique specifically designed to embrace nonlinear and heterogeneous dynamics that are driven by information.

The insights highlight an important implication for policy design. The findings suggest that policies targeting income inequality may also need to consider corruption dynamics, while anti-corruption strategies may benefit from addressing structural market

[1] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3217784.

concentration. Moreover, the findings underscore the value of adopting information-theoretic tools in macro-institutional research, offering new avenues for analysing complex causal systems where traditional econometric methods may be less effective in capturing nonlinear and asymmetric dynamics.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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