Master's Thesis:

Trade Openness and Inflation Dynamics: A Panel Data Analysis

by

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We acknowledge and respect the Lekwungen peoples on whose traditional territory the university stands and the Songhees, Esquimalt, and WSÁNEĆ peoples whose historical relationships with the land continue to this day.

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Abstract

This thesis focuses on the intricate empirical relationship between trade openness and inflation, challenging previous literature that suggests a straightforward negative correlation between the two. By employing recently developed dynamic heterogeneous panel methods and constructing a comprehensive panel dataset, which encompasses a spectrum of economic, political, and financial indicators, as well as two proxies for openness, we offer a nuanced perspective on the topic. Central to our findings is the critical role of allowing cross-sectional dependence in panel data, which has been frequently overlooked in past studies. Our analysis reveals a multifaceted relationship, where the influence of trade openness on inflation is dynamic and ambiguous in its direction. While traditional openness metrics remain useful, multidimensional proxies, such as the KOF trade openness index, have the potential to provide richer insights. Our results underscore the need for a thorough analysis and robust methodologies when exploring this economic relationship, suggesting that the dynamics of trade and inflation are more complex than previously assumed.

Keywords: Inflation; Cross-section dependence; Trade Openness, Dynamic Common Correlated Effects.

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1 Introduction

The relationship between trade openness and inflation has been a topic of considerable academic interest, prompting debates and investigations among economists for years. Traditional theories and observations often imply a straightforward negative relationship between the two, suggesting that as countries open up to international trade, they experience downward pressures on inflation. However, is the relationship truly as simplistic as it is often portrayed? Or are there deeper, more intricate dynamics at play that might challenge these conventional views?

Our research seeks to critically assess and unravel these dynamics, positing that the assumed simple negative relationship might not capture the full picture. We argue that a primary pitfall in understanding this relationship arises from the frequent omission of cross-sectional dependence in panel data analysis. This oversight, we believe, might be masking the true nature of the relationship between trade openness and inflation.

Trade, in the modern globalized era, is multifaceted. By using two distinct proxies — the ratio of total trade (imports plus exports) to GDP, and the KOF trade openness index — we aim to offer a nuanced perspective on trade's impact.[1] The first, a direct measure, encapsulates the sheer volume of trade relative to a country's economic size. The second, more comprehensive in nature, considers not just the volume, but the various aspects of openness, allowing for a more encompassing understanding.

The economic literature is replete with studies exploring the trade-inflation nexus. Alfaro, 2005, Bowdler, 2009, Jafari Samimi et al., 2012, Bianchi and Civelli, 2015 and others have provided invaluable insights that serve as the foundation upon which our research is built. However, our literature review suggests that there is still a significant gap in understanding, especially when it comes to accounting for cross-sectional dependence.

Our dataset, as outlined in Table 2, is both extensive and detailed, ensuring a comprehensive insight into the subject. By setting rigorous criteria, such as excluding countries with fewer than 20 observations and treating extreme inflation rates as outliers, we ensure the robustness of our findings. Indeed, it is pivotal to approach macro-panel data with methods tailored to its unique characteristics. Traditional estimators, primarily designed for micro datasets, might fall short in capturing the realities of macro-panel data— especially with issues like cross-section dependence errors, slope coefficient heterogeneity across units, and significant time-series dimensions.

In light of these challenges, our research employs the Dynamic Common Correlated Effects (DCCE) estimator, acclaimed for its efficacy in large cross-section and time-series dimensions. Notably, this estimator's robustness to unknown forms of cross-sectional

[1] The KOF openness index is published by the KOF ("Konjunkturforschungsstelle") Swiss Economic Institute.

dependence is particularly valuable given the period under study— marked by increasing economic integration and shared global shocks, from oil crises to financial downturns.

Our chosen method's flexibilty is anchored in the long-observed persistence of inflation. Recognizing this, we aim to unpack the relationship between current inflation rates and changes in trade openness. This perspective, coupled with the DCCE estimator, ensures a fine-grained understanding, highlighting not just immediate impacts, but lingering influences as well. Moreover, considering the innate heterogeneity across countries— in their economic structures, policies, and historical contexts— our use of the DCCE estimator allows for such variations, offering insights that are both broad and tailored.

In summary, this essay embarks on an exploration into the intricate relationship between trade openness and inflation, challenging conventional understandings, and drawing on robust methodologies to provide more contemporaneous insights. Our aim is not just to add another perspective to the academic discourse, but to provide a comprehensive, refined, and empirically-backed insight into an issue of significant economic relevance.

2 Literature review

The relationship between trade openness and inflation has attracted the interest of many scholars and economic policymakers. The range of studies on this topic exhibits diverse findings, methodologies, and time frames. From the complexities of exchange rate regimes to the particularities of globalization and the Phillips Curve, the various researches often present a mosaic of interpretations that challenge and complement each other.

Starting with Romer, 1993, this author tries to model the interplay between trade openness and inflation in an open economy by extending the classical dynamic inconsistency framework of monetary policy. This application integrates the degree of trade openness into a standard model to demonstrate its impact on equilibrium inflation. In the standard closed-economy model, the relationship between output (denoted by y) and inflation (π) is typically represented as:

$$y = y^* + \lambda(\pi - \pi^e), \tag{1}$$

where y^* represents the natural rate of output, π^e is the expected inflation, and λ is a positive parameter that measures the responsiveness of output to unanticipated inflation Romer, 1993.

In an open economy, the influence of trade openness (α, say) alters the above dynamics. The degree of openness affects both the CPI inflation (π_{CPI}) and the real exchange rate (e):

$$\pi_{CPI} = \alpha(e + \pi^*) + (1 - \alpha)p, \tag{2}$$

$$e + \pi^* - p = \alpha\lambda(y - y^*), \tag{3}$$

where π^* is the foreign inflation rate, and p is the domestic inflation rate (Romer, 1993).

These modifications imply that in more open economies, where α is higher, the trade-offs faced by policy-makers are significantly altered. A higher degree of openness typically leads to a reduced incentive for monetary expansion due to the enhanced impact of such policies on the real exchange rate and the consequent depreciation. Thus, more open economies tend to exhibit lower levels of equilibrium inflation, a theoretical prediction that aligns with empirical observations (Romer, 1993).

Drawing on empirical evidence (using limited cross-country data), Romer, 1993 reinforces this theoretical stance by analyzing data from multiple countries. His empirical findings highlight a consistent negative relationship between trade openness and inflation. Countries that are more open to international trade tend to have lower inflation rates compared to their less open counterparts.

Turning to the paper "Inflation, Openness, and Exchange-Rate Regimes: The Quest for Short-Term Commitment" by Laura Alfaro Alfaro, 2005, the exploration into the relationship between openness, inflation, and exchange-rate regimes for a large number of countries revealed an intriguing duality. While cross-sectional analysis pinpointed a negative and significant association between inflation and openness, the panel data analysis, accounting for fixed effects, suggests a much weaker relationship.

In this study, a model is presented to analyze the relationship between inflation, economic openness, and exchange-rate regimes. The key equation in this model is as follows:

$$\log(\text{Inflation}_{it}) = \beta_1 \text{Openness}_{it} + \beta_2 \text{ExchangeRateRegime}_{it} + \beta_3 \text{Controls}_{it} + \gamma_i + \kappa_t + \mu_{it} \tag{4}$$

where $\log(\text{Inflation}_{it})$ represents the logarithm of the inflation rate for country i at time t, Openness_{it} is a measure of the degree of openness of the economy of country, $\text{ExchangeRateRegime}_{it}$ denotes the exchange-rate regime adopted, Controls_{it} includes other control variables relevant to the model, γ_i and κ_t are country and year fixed effects, respectively, and μ_{it} is the error term.

This equation serves as a basis to empirically investigate the impact of economic openness and exchange-rate regime choice on inflation rates across different countries and time periods. The study finds that countries with pegged exchange-rate regimes tend to have better inflation performance, suggesting the importance of these regimes as a commitment mechanism in controlling inflation.

Contrastingly, the study by Bianchi and Civelli, 2015 used a time-varying coefficients VAR model to probe the implications of globalization on inflation. Their findings presented a convoluted picture, highlighting the absence of a clear common trend in the correlations between output gaps, inflation, and globalization. Their work emphasizes the distinctive effects of trade integration on inflation dynamics, suggesting the magnitude of openness changes as the key determinant.

On the other hand, Bowdler, 2009 employs a vector autoregression (VAR) approach to study the dynamics of inflation, economic openness, and exchange-rate regimes. The core of the model is a Phillips Curve, which is represented in a VAR framework. The key equations of this model are presented as follows:

$$\Pi_t = \alpha + \beta \Pi_{t-1} + \gamma X_t + \delta ER_t + \epsilon_t \tag{5}$$

where Π_t is the rate of inflation at time t, Π_{t-1} is the lagged inflation, capturing the inertia in inflation dynamics, X_t represents the vector of explanatory variables including output gap, economic openness, and other relevant macroeconomic factors, ER_t denotes the exchange rate regime variable and ϵ_t is the error term capturing unobserved factors.

This model allows for an analysis of the impact of economic openness and the choice of exchange-rate regime on the inflationary process. The VAR framework accommodates dynamic interactions among these variables, providing a comprehensive view of their temporal relationships. The study discovered a weak negative relationship between openness and the output-inflation trade-off, stronger under flexible exchange rate regimes. However, these results presented a stark contrast to earlier research findings, which had underscored a strong positive effect of openness on the sacrifice ratio.

Delving deeper into the volatility aspect, Bowdler and Malik, 2017 provided a comprehensive analysis of the relationship between trade openness and inflation volatility. Their approach, utilizing the generalized method of moments (GMM) technique, sheds light on the negative impact of openness on inflation volatility, reaffirming the notion that countries more open to trade exhibit reduced inflation volatility. The key econometrics representation in their analysis can be expressed as follows:

$$\Delta \text{VolInf}_{it} = \alpha + \sum_{j=1}^{p} \beta_j \Delta \text{VolInf}_{i,t-j} + \gamma \text{Openness}_{it} + \varepsilon_{it} \tag{6}$$

where ΔVolInf_{it} is the change in the volatility of inflation rate computed over 8 windows of 20 quarters, for country i at time t, α is a constant term, β_j are the coefficients for lagged inflation rate volatility, capturing the dynamic nature of inflation, Openness_{it} represents the degree of openness of the economy of country i at time t and ε_{it} is the error term.

In their empirical approach, Bowdler and Malik, 2017 employ panel data to estimate the relationship between inflation volatility and openness, controlling for the dynamic nature of inflation through the inclusion of lagged terms. Their findings suggest a significant and negative relationship between openness and inflation volatility, implying that more open economies tend to experience less volatile inflation rates. The study provides valuable insights into the role of economic openness in shaping inflation dynamics, highlighting the potential benefits of open trade and financial policies in stabilizing inflation.

Temple, 2002, in turn, presents a thought-provoking exploration of the output-inflation trade-off. His research found no strong correlation between openness and the sacrifice ratio, introducing a puzzle into the openness-inflation dynamic. His suggestion that inflation may be perceived as more costly in open economies due to real exchange rate variability further enriched the debate.

In this work, a careful exploration of the interplay between openness, inflation, and the Phillips curve is presented. A key aspect of Temple, 2002's model is the incorporation of the Phillips curve, traditionally expressed as:

$$\pi_t = \beta \mathrm{E}_t[\pi_{t+1}] + \gamma(y_t - \bar{y}) + \varepsilon_t, \tag{7}$$

where π_t is the inflation rate at time t, $\mathrm{E}_t[\pi_{t+1}]$ is the expected inflation rate at time $t+1$, y_t is the output at time t, $\bar{y}$ is the natural level of output, and ε_t is the error term. The coefficients β and γ capture the responsiveness of inflation to expected future inflation and the output gap, respectively.

Temple, 2002 extends this framework by incorporating the degree of openness into the model. Openness is posited to affect both the sensitivity of inflation to the output gap and the formation of inflation expectations. This leads to a VAR model where the coefficients are functions of the openness level:

$$\pi_t = \beta(o_t)\mathrm{E}_t[\pi_{t+1}] + \gamma(o_t)(y_t - \bar{y}) + \varepsilon_t, \tag{8}$$

with o_t representing the openness at time t. The functions $\beta(o_t)$ and $\gamma(o_t)$ indicate how the relationships in the Phillips curve adjust with varying levels of economic openness.

The puzzle that Temple, 2002 addresses arises from the empirical observation that higher openness is often associated with lower inflation, yet traditional Phillips curve models do not clearly predict this relationship. His VAR approach attempts to reconcile this discrepancy by suggesting that openness influences the dynamic interaction between output and inflation.

In a broad panel data approach, Sachsida et al., 2003 explored the relationship between trade openness and inflation for a vast number of countries over an extensive period. The following model is estimated:

$$\log(\text{Inflation}_{it}) = a_i + b(\text{Openness}_{it}) + \varepsilon_{it} \tag{9}$$

where $\log(\text{Inflation}_{it})$ represents the natural logarithm of the implicit GDP deflator, indicating the inflation rate for country i at time t, a_i is a constant specific to each country or group of countries, Openness_{it} denotes the degree of trade openness for country i at time t, measured as the rate of imports relative to GDP, b is the slope coefficient, indicating the effect of trade openness on inflation and ε_{it} is the error term. This model is used to empirically test the hypothesis that greater trade openness is associated with lower inflation rates. Their research lent support to the negative relationship between trade openness and inflation, emphasizing that this relationship transcends specific groups of countries or distinct time frames.

Lastly, Jafari Samimi et al., 2012 enriched the literature by offering a multifaceted investigation into the relationship between trade openness, economic globalization, and inflation. Their innovative dual-model approach brought to light the positive and significant relationship between trade openness and inflation, contradicting the Romer (1993) hypothesis. However, their findings using the KOF index pivoted the narrative, underscoring that economic globalization leads to reduced inflation.

In summary, the literature on the relationship between trade openness and inflation offers a rich tapestry of findings, methodologies, and interpretations. To further streamline the insights, the following table categorizes the various studies based on their main findings: globalization reduces inflation. This synthesis underscores the complexity of the trade openness-inflation nexus and highlights the need for continuous exploration, especially as the global economic landscape continues to evolve.

3 Methodology

Panel data consist of observations on many individual economic units over two or more periods. The individual units are usually referred to as cross-sectional units, and in economic and finance applications are typically represented by single individuals, firms, returns on individual securities, industries, regions, or countries.

In recent years, panel data sets have become widely available to empirical researchers. Examples of such data sets in the US include the Panel Study of Income Dynamics (PSID), collected by the Institute for Social Research at the University of Michigan, and the National Longitudinal Surveys of Labor Market Experience (NLS), from the Center for Human Resource Research at Ohio State University. We have used Pesaran, 2015 for the methodology section.

Table 1: Summary of studies on the relationship between trade openness and inflation.

Study	Relationship	Main Conclusion
Romer, David (1993)	Negative	More open economies experience lower inflation rates due to susceptibility to international competition and external economic forces
Alfaro (2005)	Negative (Cross-sectional)	Fixed exchange rates limit short-term inflation
Bianchi & Civelli (2015)	Ambiguous	Effects of openness require substantial changes to manifest
Bowdler (2009)	Weakly Negative	Openness influences the output-inflation trade-off
Bowdler & Malik (2017)	Negative	Trade openness reduces inflation volatility
Temple (2002)	No Strong Correlation	Openness-inflation presents a puzzle
Sachsida et al. (2003)	Negative	Openness leads to reduced inflation
Jafari Samimi et al. (2012)	Positive (Trade) / Negative (KOF)	Economic globalization reduces inflation

3.1 Linear panels with strictly exogenous regressors

Let y_{it} be the observation on the i^{th} cross-sectional unit at time t for $i = 1, 2, \ldots, N; t = 1, 2, \ldots, T$, and assume it is generated by the following panel data regression model

$$y_{it} = \alpha_i + \beta' x_{it} + u_{it} \tag{10}$$

where x_{it} is a $k \times 1$ vector of observed individual specific regressors on the i^{th} cross-sectional unit at time t, u_{it} is the error term, β is a k-dimensional vector of unknown parameters, and α_i denotes an unobservable, unit-specific effect. Note that α_i is time-invariant, and it accounts for any individual-specific effect that is not included in the regression (Mundlak, 1978).

3.1.1 Pooled OLS estimator

This estimator assumes that the intercepts are homogeneous, namely $\alpha_i = \alpha$, for all i. In this case, the panel data model reduces to

$$y_{it} = \alpha + \beta' x_{it} + u_{it} \tag{11}$$

and α and β can be estimated by the OLS procedure. The resultant estimator of β is known as pooled OLS and is given by

$$\hat{\beta}_{OLS} = \left[\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x})(x_{it} - \bar{x})'\right]^{-1}\left[\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x})(y_{it} - \bar{y})\right], \tag{12}$$

where

$$\bar{x} = (NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T} x_{it}, \quad \bar{y} = (NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it} \tag{13}$$

and assuming that $\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x})(x_{it} - \bar{x})'$ is a nonsingular matrix.

3.1.2 Fixed effects estimator

The FE estimator considers the intercepts as fixed parameters to be estimated along with β. In this case, the panel data model is

$$y_{it} = \alpha_i + \beta' x_{it} + u_{it} \tag{14}$$

We note that the presence of individual effects, α_i, introduces correlation between the regressors and the error term. This is because the α_i's are time-invariant and correlated with any variable with a non-zero time-average. This includes most of the regressors we are interested in. Therefore, OLS applied to the model above yields inconsistent estimators. To eliminate the individual effects, α_i, we can transform the model by subtracting from both sides of the equation the time averages over T:

$$y_{it} - \bar{y}_{i.} = \beta'(x_{it} - \bar{x}_{i.}) + (u_{it} - \bar{u}_{i.}) \tag{15}$$

The resultant estimator of β is known as the within or the fixed effects (FE) estimator and is given by

$$\hat{\beta}_{FE} = \left[\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x}_{i.})(x_{it} - \bar{x}_{i.})'\right]^{-1}\left[\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x}_{i.})(y_{it} - \bar{y}_{i.})\right] \tag{16}$$

where

$$\bar{x}_{i.} = T^{-1}\sum_{t=1}^{T} x_{it}, \quad \bar{y}_{i.} = T^{-1}\sum_{t=1}^{T} y_{it} \tag{17}$$

Under the FE specification, we assume that conditional on the individual effects α_i, the regressors x_{it} are strictly exogenous, but do not impose any restrictions on the fixed-effects. More formally, we continue to maintain Assumptions P1, P4, and P5, but replace Assumptions P2 and P3 with the following:

Assumption P2′: The regressors, x_{it}, are either deterministic and bounded, namely $\|x_{it}\| < K < \infty$, or they satisfy the moment conditions $E\left\|(x_{it} - \bar{x}_i)(x_{jt'} - \bar{x}_j)'\right\| < K < \infty$, for all i, j, t, and t', where $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$.

Assumption P3′: The $k \times k$ matrix $Q_{\mathrm{FE},NT}$ defined by

$$Q_{\mathrm{FE},NT} = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)'$$

is positive definite for all N and T, and as N and/or $T \to \infty$.

3.1.3 Instrumental Variables (IV) and Generalized Method of Moments (GMM), Arellano and Bond

In this section, we explore the estimation of economic relationships that exhibit dynamic characteristics in panel data. While previous analysis focused on panels with exogenous regressors, we now address cases where the data-generating process includes lagged dependent variables. In such situations, the assumption of strict exogeneity of the regressors is violated and OLS and FE estimators are biased (Pesaran, 2015).

A vast amount of literature has been developed on Instrumental Variables (IV) and the Generalized Method of Moments (GMM) estimation of dynamic panel data models. Arellano and Bond (1991) argue that additional instruments can be obtained in a dynamic panel data model if one exploits the orthogonality conditions that exist between lagged values of y_{it} and the disturbances v_{it}. Hence, the authors suggest using a GMM approach based on all available moment conditions.

$$y_{i3} - y_{i2} = \lambda(y_{i2} - y_{i1}) + \beta'\Delta x_{i3} + \Delta u_{i3} \tag{18}$$
$$y_{i4} - y_{i3} = \lambda(y_{i3} - y_{i2}) + \beta'\Delta x_{i4} + \Delta u_{i4} \tag{19}$$
$$y_{i5} - y_{i4} = \lambda(y_{i4} - y_{i3}) + \beta'\Delta x_{i5} + \Delta u_{i5} \tag{20}$$
$$\vdots$$
$$y_{iT} - y_{i,T-1} = \lambda(y_{i,T-1} - y_{i,T-2}) + \beta'\Delta x_{iT} + \Delta u_{iT} \tag{21}$$

In equation (18), the valid instrument for $(y_{i2} - y_{i1})$ is y_{i1}; in equation (19) valid instruments for $(y_{i3} - y_{i2})$ are y_{i1} and y_{i2}, while in (20) they are y_{i1}, y_{i2}, and y_{i3}, and so forth until equation (21), where the valid instruments are y_{i1}, y_{i2}, ..., $y_{i,T-2}$. Hence, an additional valid instrument is added with each additional time period. Clearly, the appropriate instruments for Δx_{it} are themselves, since, by assumption, x_{it} are strictly exogenous. Hence, there is a total of $T(T-1)/2$ available instruments or moment conditions for $\Delta y_{i,t-1}$ that are given by

$$E[y_{is}(\Delta y_{it} - \lambda\Delta y_{i,t-1} - \beta'\Delta x_{it})] = 0, \quad s = 0, 1, \ldots, t-2; \quad t = 2, 3, \ldots, T$$

To deal with the serial correlation in the transformed disturbances, Δu_{it}, Arellano and Bond, 1991 apply the GMM method to obtain:

$$\hat{\gamma}_{\text{GMM}} = (G'ZS_N Z'G)^{-1}G'ZS_N Z'\Delta y \tag{22}$$

where $\hat{\gamma}_{\text{GMM}} = (\hat{\lambda}_{\text{GMM}}, \hat{\beta}'_{\text{GMM}})'$, $G = (\Delta y_{-1}, \Delta X)$, $Z_{i.} = (W_i, \Delta x_{i.})$ and S_N refers to the weighting matrix used in the GMM estimation procedure for dynamic panel data models. Alternative choices for the weights S_N give rise to a set of GMM estimators based on the moment conditions, It is possible to show that the asymptotically optimal weights are given by

$$S_N = \left(\sum_{i=1}^{N} Z'_{i.}\hat{u}_{i.}\hat{u}'_{i.}Z_{i.}\right)^{-1},$$

with $Z_{i.} = (W_i, \Delta x_{i.})$, and $\hat{u}_{i.}$ are the residuals from a consistent estimate.

3.2 Slope heterogeneity

Pooled estimators assume that the slope coefficients (β_i) are the same for all units in the panel, which is not the case in heterogeneous panels. The fixed-effects (FE) estimators, which aim to account for individual-specific fixed effects, also suffer from inconsistency in the presence of slope heterogeneity. When slope heterogeneity exists but is ignored, applying pooled or FE estimators can lead to spurious inference and misleading results.

Consider the autoregressive distributed lag (ARDL)$(p, \underbrace{(q, q, \ldots, q)}_{k\text{-times}})$ model defined as:

$$y_{it} = \alpha_i + \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} x_{i,t-j} + u_{it}, \quad \text{for } i = 1, 2, \ldots, N \tag{23}$$

where x_{it} is a k-dimensional vector of explanatory variables for group i, α_i represent the fixed-effects; the coefficients of the lagged dependent variables, λ_{ij}, are scalars; and δ_{ij} are k dimensional coefficient vectors. In the following, we assume that the disturbances u_{it}, $i = 1, 2, \ldots, N$; $t = 1, 2, \ldots, T$, are independently distributed across i and t, with zero means, variances σ_i^2, and are distributed independently of the regressors x_{it}.

The error correction representation of the above ARDL model is:

$$\Delta y_{it} = \alpha_i + \phi_i y_{i,t-1} + \beta'_i x_{it} + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta'^*_{ij} \Delta x_{i,t-j} + u_{it} \tag{24}$$

where the coefficients ϕ_i, β_i, λ^*_{ij}, and δ'^*_{ij} are defined as:

$$\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}), \tag{25}$$

$$\beta_i = \sum_{j=0}^{q} \delta_{ij}, \tag{26}$$

$$\lambda_{ij}^* = - \sum_{m=j+1}^{p} \lambda_{im}, \quad j = 1, 2, \dots, p-1, \tag{27}$$

$$\delta_{ij}'^* = - \sum_{m=j+1}^{q} \delta_{im}, \quad j = 1, 2, \dots, q-1. \tag{28}$$

If the roots of the polynomial $f_i(z) = 1 - \sum_{j=1}^{p} \lambda_{ij} z^j = 0$, for $i = 1, 2, \dots, N$, fall outside the unit circle, then the ARDL$(p, q, q, \dots, q)$ model is stable. This condition ensures that $\phi_i < 0$, and that there exists a long-run relationship between y_{it} and x_{it} defined by $y_{it} = \theta_i x_{it} + \eta_{it}$ for each $i = 1, 2, \dots, N$, where η_{it} is $I(0)$, and θ_i are the long-run coefficients on $X_{i.}$, $\theta_i = -\beta_i/\phi_i$. Traditional estimation procedures for pooled models, such as the fixed effects estimator or the IV/GMM approaches, can produce inconsistent and potentially misleading estimates of the average value of the parameters in dynamic panel data models unless the slope coefficients are homogeneous(Pesaran, 2015).

3.2.1 Mean group estimator of dynamic heterogeneous panels

Consider a dynamic model of the form:

$$y_{it} = \lambda_i y_{i,t-1} + x_{it}' \beta_i + u_{it}, \quad i = 1, 2, \dots, N; \quad t = 1, 2, \dots, T$$

where x_{it} is a $k \times 1$ vector of exogenous variables, and the error term u_{it} is assumed to be independently, identically distributed over t with mean zero and variance σ_i^2, and is independent across i. Let $\psi_i = (\lambda_i, \beta_i')'$. Further assume that ψ_i is independently distributed across i with

$$E(\psi_i) = \psi = (\lambda, \beta')', \quad E[(\psi_i - \psi)(\psi_i - \psi)'] = \Delta$$

Rewriting $\psi_i = \psi + \eta_i$, we have:

$$E(\eta_i) = 0, \quad E(\eta_i \eta_j') = \begin{cases} \Delta & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$$

Although we may maintain the assumption that $E(\eta_i x_{it}') = 0$, we can no longer assume that $E(\eta_i y_{i,t-1}) = 0$. Through continuous substitutions, we have

$$y_{i,t-1} = \sum_{j=0}^{\infty}(\lambda + \eta_{i1})^j (x'_{i,t-j-1})(\beta + \eta_{i2}) + \sum_{j=0}^{\infty}(\lambda + \eta_{i1})^j u_{i,t-j-1}$$

where $\eta_i = (\eta_{i1}, \eta'_{i2})'$. It follows that $E(\eta_i y_{i,t-1}) \neq 0$ (Pesaran, 2015).

The violation of the independence between the regressors and the individual effects, η_i, implies that the pooled least squares regression of y_{it} on $y_{i,t-1}$, and x_{it} will yield inconsistent estimates of ψ, even for sufficiently large T and N. Pesaran and Smith, 1995 have noted that, as $T \to \infty$, the least squares regression of y_{it} on $y_{i,t-1}$ and x_{it} yields a consistent estimator of ψ_i, $\hat{\psi}_i$. Hence, the authors suggest a Mean Group (MG) estimator of ψ by taking the average of $\hat{\psi}_i$ across i,

$$\hat{\psi}_{MG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\psi}_i$$

where

$$\hat{\psi}_i = (W'_{i.}W_{i.})^{-1}W'_{i.}y_{i.}$$

with $W_{i.} = (y_{i,-1}, X_{i.})$ and $y_{i.,-1} = (y_{i0}, y_{i1}, \ldots, y_{iT-1})'$.

Note that, for finite T, $\hat{\psi}_i$ for ψ_i is biased, with a bias of order $1/T$ Kiviet and Phillips, 1993 Hsiao et al., 1998 have shown that the MG estimator is asymptotically normal for large N and large T so long as $\sqrt{N/T} \to 0$ as both N and T tend to infinity.

3.3 Panels with cross-sectional dependence

The problem of estimating panels with cross-sectional error dependence is further complicated when the assumption of strict exogeneity of unit-specific regressors is relaxed(Pesaran, 2015). One such example is the panel data model with lagged dependent variables and unobserved common factors (possibly correlated with regressors). This model is represented by the equation

$$y_{it} = \lambda_i y_{i,t-1} + \beta_i x_{it} + u_{it} \tag{29}$$

$$u_{it} = \gamma'_i f_t + e_{it} \tag{30}$$

where $i = 1, 2, ..., N$ and $t = 1, 2, ..., T$. Here, f_t is a vector of unobserved common factors that affect all cross-sectional units, but vary over time. These factors are included to account for any unobserved heterogeneity that might be correlated across different units in the panel. It is assumed that $|\lambda_i| < 1$ and the dynamic processes have started a long time in the past.

To handle the issue of coefficient heterogeneity, the distinction between the cases of homogeneous and heterogeneous coefficients is made. The mean coefficients $\lambda = E(\lambda_i)$ and $\beta = E(\beta_i)$ are the objects of interest in the heterogeneous case. Defining the vector of regressors $\zeta_{it} = (y_{i,t-1}, x'_{it})'$ and the corresponding parameter vector $\pi_i = (\lambda_i, \beta'_i)'$, the equation can be written as:

$$y_{it} = \pi'_i \zeta_{it} + u_{it} \tag{31}$$

3.3.1 Common factor models

Let z_{it} represent a vector of observed variables in a common factor model for panel data. The model is structured to account for the presence of unobserved common factors that influence all cross-sectional units (such as individuals, firms, or countries), as well as idiosyncratic shocks unique to each unit. Consider the m factor model for z_{it},

$$z_{it} = \gamma_{i1} f_{1t} + \gamma_{i2} f_{2t} + \cdots + \gamma_{im} f_{mt} + e_{it}, \qquad i = 1, 2, \ldots, N, \tag{32}$$

which can be written more compactly as

$$z_t = \Gamma f_t + e_t, \tag{33}$$

where $f_t = (f_{1t}, f_{2t}, \ldots, f_{mt})'$, $e_t = (e_{1t}, e_{2t}, \ldots, e_{Nt})'$, and $\Gamma = (\gamma_{ij})$, for $i = 1, 2, \ldots, N$, $j = 1, 2, \ldots, m$, is an $N \times m$ matrix of fixed coefficients, known as factor loadings. The common factors, f_t, simultaneously affect all cross-sectional units, albeit with different degrees as measured by $\gamma_i = (\gamma_{i1}, \gamma_{i2}, \ldots, \gamma_{im})'$.

Assumption CF.1: The $m \times 1$ vector f_t is a zero mean covariance stationary process, with absolutely summable autocovariance, distributed independently of e'_{it} for all i, t, t', such that $E(f^2_{lt}) = 1$ and $E(f_{lt} f_{l't}) = 0$, for $l \neq l' = 1, 2, \ldots, m$.

Assumption CF.2: $\text{Var}(e_{it}) = \sigma^2_i < K < \infty$, e_{it} and e_{jt} are independently distributed for all $i \neq j$ and for all t. Specifically, $\max_i(\sigma^2_i) = \sigma^2_{max} < K < \infty$.

Assumption CF.1 is an identification condition since it is not possible to separately identify f_t and Γ (Pesaran, 2015).

The covariance of z_t is given by

$$E(z_t z'_t) = \Gamma\Gamma' + V, \tag{34}$$

where V is a diagonal matrix with elements σ^2_i on the main diagonal.

The factor model that allows the idiosyncratic shocks, e_{it}, to be cross-sectionally weakly correlated is known as the approximate factor model. In general, the correlation patterns of the idiosyncratic errors can be characterized by

$$e_t = R\epsilon_t, \tag{35}$$

where $\epsilon_t = (\epsilon_{1t}, \epsilon_{2t}, \dots, \epsilon_{Nt})' \sim (0, I_N)$. In the case of this formulation $V = RR'$, which is no longer diagonal when R is not diagonal, further identification restrictions are needed so that the factor specification can be distinguished from the cross-sectional dependence assumed for the idiosyncratic errors. A leading example of R arises in the context of the first-order spatial autoregressive, SAR(1) model, defined by

$$e_t = \rho W e_t + \Lambda\epsilon_t, \tag{36}$$

where Λ is a diagonal matrix with strictly positive and bounded elements, $0 < \sigma_i < \infty$, ρ is a spatial autoregressive coefficient, and the matrix W is a 'connection' or 'spatial' weight matrix which is taken as given. Assuming that $(I_N - \rho W)$ is invertible, we then have $R = (I_N - \rho W)^{-1}\Lambda$.

In the spatial literature, W is assumed to have non-negative elements and is typically row-standardized so that $\|W\|_\infty = 1$. Under these assumptions, $|\rho| < 1$ ensures that $|\rho|\|W\|_\infty < 1$, and we have

$$\begin{aligned}
\|R\|_\infty &\leq \|\Lambda\|_\infty \|I_N + \rho W + \rho^2 W^2 + \cdots\|_\infty \\
&\leq \|\Lambda\|_\infty (1 + |\rho|\|W\|_\infty + |\rho|^2\|W\|_\infty^2 + \cdots) = \frac{\|\Lambda\|_\infty}{1 - |\rho|\|W\|_\infty} < K < \infty,
\end{aligned}$$

where $\|\Lambda\|_\infty = \max_i(\sigma_i) < \infty$. Similarly, $\|R\|_1 < K < \infty$, if it is further assumed that $|\rho|\|W\|_1 < 1$. In general, $R = (I_N - \rho W)^{-1}\Lambda$ has bounded row and column sum matrix norms if $|\rho| < \max(1/\|W\|_1, 1/\|W\|_\infty)$. In the case where W is a row and column stochastic matrix (often assumed in the spatial literature) this sufficient condition reduces to $|\rho| < 1$, which also ensures the invertibility of $(I_N - \rho W)$.

To ensure that the factor component defined above represents strong cross-sectional dependence, it is sufficient that the absolute column sum matrix norm of $\|\Gamma\|_1 = \max_{j\in\{1,2,\dots,N\}} \sum_{i=1}^N |\gamma_{ij}|$ rises with N at the rate N, and $\lim_{N\to\infty}(N^{-1}\Gamma'\Gamma)$ is a full rank matrix (Pesaran, 2015).

The distinction between weak and strong cross-sectional dependence in terms of factor loadings is formalized in the following definition:

The factor f_{lt} is said to be strong if

$$\lim_{N\to\infty} N^{-1} \sum_{i=1}^{N} |\gamma_{il}| = K > 0. \tag{37}$$

The factor f_{lt} is said to be weak if

$$\lim_{N\to\infty}\sum_{i=1}^{N}|\gamma_{il}| = K < \infty. \tag{38}$$

It is also possible to consider intermediate cases of semi-weak or semi-strong factors. In general, let α_l be a positive constant in the range $0 \leq \alpha_l \leq 1$ and consider the condition

$$\lim_{N\to\infty} N^{-\alpha_l}\sum_{i=1}^{N}|\gamma_{il}| = K < \infty, \text{ for } K > 0. \tag{39}$$

Strong and weak factors correspond to the two values of $\alpha_l = 1$ and $\alpha_l = 0$, respectively. For any other values of $\alpha_l \in (0, 1)$ the factor f_{lt} can be said to be semi-strong or semi-weak. It will prove useful to associate the semi-weak factors with values of $0 < \alpha_l < 1/2$, and the semi-strong factors with values of $1/2 \leq \alpha_l < 1$. In a multi-factor set up the overall exponent can be defined by $\alpha = \max(\alpha_1, \alpha_2, \ldots, \alpha_m)$.

3.3.2 Large Heterogeneous Panels with a Multifactor Error Structure

Consider the following heterogeneous panel data model:

$$y_{it} = \alpha_i' d_t + \beta_i' x_{it} + u_{it} \tag{40}$$

where d_t is an $n \times 1$ vector of observed common effects (including deterministics such as intercepts or seasonal dummies), x_{it} is a $k \times 1$ vector of observed individual-specific regressors on the i^{th} cross-sectional unit at time t, and disturbances, u_{it}, have the following common factor structure:

$$u_{it} = \gamma_i' f_t + e_{it} \tag{41}$$

in which $f_t = (f_{1t}, f_{2t}, \ldots, f_{mt})'$ is an m-dimensional vector of unobservable common factors, and $\gamma_i = (\gamma_{i1}, \gamma_{i2}, \ldots, \gamma_{im})'$ is the associated $m \times 1$ vector of factor loadings. The number of factors, m, is assumed to be fixed relative to N, and in particular $m << N$. The idiosyncratic errors, e_{it}, could be cross-sectionally weakly dependent (CWD), for example, being generated by a spatial process, or, more generally, by a weak factor structure.

For estimation purposes, as in the case of panels with group effects, the factor loadings, γ_i, could be either random or fixed unknown coefficients. We distinguish between the homogeneous coefficient case where $\beta_i = \beta$ for all i, and the heterogeneous case where β_i are random draws from a given distribution. In the latter case, we assume that the object of interest is the mean coefficients, $\beta = \mathbb{E}(\beta_i)$, for all i.

When the regressors, x_{it}, are strictly exogenous and the deviations $v_i = \beta_i - \beta$ are distributed independently of the errors and the regressors, the mean coefficients, β, can be consistently estimated using pooled as well as mean group estimation procedures. But only mean group estimation will be consistent if the regressors are weakly exogenous and/or if the deviations are correlated with the regressors/errors.

The assumption of slope homogeneity is also crucially important for the derivation of the asymptotic distribution of the pooled or the mean group estimators of β. Under slope homogeneity, the asymptotic distribution of the estimator of β generally converges at the rate of $\sqrt{NT}$, while under slope heterogeneity, the rate is $\sqrt{N}$. Given the uncertainty regarding the assumption of slope heterogeneity, non-parametric estimators of the variance matrix of the pooled and mean group estimators are proposed (Pesaran, 2015).

3.3.3 Common Correlated Effects Estimator

Pesaran (2006) introduced the Common Correlated Effects (CCE) estimation procedure which can be represented as a system of equations:

$$z_{it} = B_i' d_t + C_i' f_t + \xi_{it}, \tag{42}$$

$$\bar{z}_{wt} = \bar{B}_w' d_t + \bar{C}_w' f_t + \bar{\xi}_{wt}, \tag{43}$$

where

- z_{it} represents the dependent variable for unit i at time t.
- $\mathbf{B}_i'$ and $\mathbf{C}_i'$ are the transposed coefficient matrices specific to unit i.
- $\mathbf{d}_t$ and $\mathbf{f}_t$ are vectors of observed common factors at time t.
- ξ_{it} is the error term for unit i at time t.
- $\bar{z}_{wt}$, $\bar{\mathbf{B}}_w'$, $\bar{\mathbf{C}}_w'$, and $\bar{\xi}_{wt}$ are the weighted averages of their respective variables and coefficients.

The estimator approximates the unobservable common factors, f_t, by a linear combination of observed effects, d_t, and cross-section averages of the dependent variable, y_{wt}, and the individual-specific regressors, x_{wt}:

$$f_t = (\bar{C}_w \bar{C}_w')^{-1} \bar{C}_w (\bar{z}_{wt} - \bar{B}' d_t - \bar{\xi}_{wt}). \tag{44}$$

Two alternative estimators, the CCE Mean Group (CCEMG) and the CCE Pooled (CCEP) are proposed. The CCEMG is an average of the estimators of the individual slope coefficients:

$$\hat{\beta}_{\text{CCEMG}} = N^{-1} \sum_{i=1}^{N} \hat{\beta}_{\text{CCE},i}, \tag{45}$$

where $\hat{\beta}_{\text{CCE},i} = (X_i' \bar{M}_w X_i)^{-1} X_i' \bar{M}_w y_i$. The CCEP estimator is given by:

$$\hat{\beta}_{\text{CCEP}} = (\sum_{i=1}^{N} w_i X_i' \bar{M}_w X_i)^{-1} \sum_{i=1}^{N} w_i X_i' \bar{M}_w y_i. \tag{46}$$

The advantage of the non-parametric estimators Σ_{CCEMG} and Σ_{CCEP} is that they do not require knowledge of the form of weak cross-sectional dependence of e_{it}, nor the knowledge of serial correlation of e_{it}.

The CCE continues to be applicable even if the rank condition is not satisfied. However, the asymptotic distribution of $\hat{\beta}_{\text{CCEMG}}$ and $\hat{\beta}_{\text{CCEP}}$ depends on nuisance parameters when slopes are homogeneous, including the nature of cross-section correlations of e_{it} and their serial correlation structure.

3.3.4 Dynamic CCE Estimators

The dynamic panel data model with lagged dependent variables and unobserved common factors is described by:

$$\begin{aligned} y_{it} &= \lambda_i y_{i,t-1} + \beta_i^T x_{it} + u_{it} \\ u_{it} &= \gamma_i^T f_t + e_{it} \end{aligned} \tag{47}$$

for $i = 1, 2, \ldots, N$; $t = 1, 2, \ldots, T$. The dynamic process is assumed to have started a long time in the past, and $|\lambda_i| < 1$. The heterogeneous case, where λ_i and β_i are randomly distributed across units, is of interest. The model is rewritten as:

$$y_{it} = \pi_i^T \zeta_{it} + u_{it} \tag{48}$$

where $\zeta_{it} = (y_{i,t-1}, x_{it}^T)^T$ and $\pi_i = (\lambda_i, \beta_i^T)^T$.

The Dynamic Common Correlated Effects (CCE) approach proposed by Pesaran, 2004 is designed for dynamic panels with heterogeneous coefficients and weakly exogenous regressors. The mean coefficients can be estimated consistently unless f_t is serially uncorrelated. A lagged dependent variable amongst the regressors leads to a well-known time series bias, the full rank condition becomes necessary for consistent estimation, and dynamics and coefficient heterogeneity interact.

The least squares estimates of π_i based on the dynamic CCE regressions, denoted as $\hat{\pi}_i = (\hat{\lambda}_i, \hat{\beta}_i^T)^T$, and the mean group estimate of $\pi = E(\pi_i)$ based on $\hat{\pi}_i$ are introduced:

$$\hat{\pi}_i = (\tilde{\Xi}_i^T \bar{M}_q \tilde{\Xi}_i)^{-1} \tilde{\Xi}_i^T \bar{M}_q \tilde{y}_i \tag{49}$$

The mean group estimator of $\pi = E(\pi_i) = (\lambda, \beta^T)^T$ is given by:

$$\hat{\pi}_{MG} = \frac{1}{N} \sum_{i=1}^{N} \hat{\pi}_i \tag{50}$$

This estimator is consistent for π_i and π under certain conditions.

However, the CCEMG estimator suffers from the well-known time series bias and tests based on it tend to be over-sized, unless T is sufficiently large. The situation is different if the parameter of interest is the mean coefficient of the lagged dependent variable (λ).

The dynamic CCE approach, proposed by Chudik and Pesaran, 2015, extends the original CCE approach to dynamic panels with heterogeneous coefficients and weakly exogenous regressors. Including a lagged dependent variable among the regressors has three consequences for the estimation of mean coefficients: time series bias, necessity of the full rank condition for consistent estimation, and complications due to interaction between dynamics and coefficient heterogeneity.

The large N distributed lag relationship between the unobserved common factors and cross-sectional averages of the dependent variable and the regressors is given by:

$$\Lambda(L)\widetilde{\Gamma}' f_t = \bar{z}wt + O_p(N^{-1/2}), \tag{51}$$

where $\widetilde{\Gamma} = E(\gamma_i, \Gamma_i)$. The unit-specific dynamic CCE regressions are:

$$y_{it} = \lambda_i y_{i,t-1} + \beta_i' x_{it} + \sum_{l=0}^{p_T} \delta_{il}' \bar{z}_{w,t-l} + e_{yit}. \tag{52}$$

Chudik and Pesaran (2015a) consider the least squares estimates of $\pi_i = (\lambda_i, \beta_i')'$, denoted as $\hat{\pi}_i = (\hat{\lambda}_i, \hat{\beta}_i')'$, and the mean group estimate of $\pi = E(\pi_i)$ based on $\hat{\pi}_i$. The individual estimates, $\hat{\pi}_i$, can be written as:

$$\hat{\pi}_i = (\widetilde{\Xi}_i' \bar{M}_q \widetilde{\Xi}_i)^{-1} \widetilde{\Xi}_i' \bar{M} q \widetilde{y} i, \tag{53}$$

and the mean group estimator of $\pi = E(\pi_i) = (\lambda, \beta')'$ is given by:

$$\hat{\pi}_{MG} = \frac{1}{N} \sum_{i=1}^{N} \hat{\pi}_i. \tag{54}$$

The $\hat{\pi}_i$ and $\hat{\pi}_{MG}$ estimators are consistent for π_i and π, respectively, under certain conditions. The small T sample properties of the CCEMG estimator of λ remain challenging, with bias-correction procedures like the half-panel jackknife providing some improvement, but not fully addressing size distortion when T is small.

4 Empirical Strategy

4.1 Data

The data shown in Table 2 gives a thorough summary of different economic, political, and financial indicators used in the analysis. The dataset we utilize combines sources from various databases, including (but not limited to) the Penn World Tables, World Development Indicators (WDI), International Monetary Fund (IMF) data, Polity IV, and the KOF Index of Globalization. It includes 184 countries, spanning the period from 1970 to 2018. The data is collected on an annual basis. It is important to note that the period of the COVID-19 pandemic is excluded from this data set, given that an event of such magnitude, but relatively shortlived and close to the end of the sample, is likely to distort the estimations.

The full list of Countries and the period of observations is presented in Appendix A. Countries with fewer than 20 observations are dropped to ensure robustness considering that the implemented methods in this study are mostly designed for samples with a sizable time series dimension, as discussed in the previous section. Additionally, observations with inflation rates exceeding 500% in a year are treated as outliers and removed since it is very unlikely to be caused by trade openness and does not add much information for our purpose.

Based on the provided indicator data, we can categorize the variables as follows:

4.1.1 External and Economic Factors

The key focus is trade openness, which we evaluate through two proxies. Firstly, "trade" is the combined value of exports and imports of goods and services as a percentage of gross domestic product. Secondly, de fact "Trade Globalisation" index (KOF), is an encompassing measure of a nation's trade engagements and global economic integration. It accounts for goods trade, services trade, and trade partner diversity. Foreign direct investment, net inflows (net_in), measures the net inflows of investment to acquire a lasting management interest in enterprises in the country by foreign investors. The export diversification index (exp_div) indicates the level of diversification in a country's exports across different products or trading partners. Furthermore, to capture the impact of economic factors on inflation outcomes, we consider GDP growth rates (gdp_growth) and government expenditure (gov_exp) and their 5 years moving average (gdp_growth_m5, gov_exp_m5) in our model.

4.1.2 Monetary Factors

Broad money growth (bro_mon_gr), represents the growth rate of broad money, which includes various forms of money like currency, demand deposits, time deposits, etc. It is related to the monetary policies implemented by the country's central bank. We also condition our inflation estimations on an exchange rate regime variable, presented with "Ex_re" that takes the value of 1 for free floating or free falling [2] regimes and 0 for the rest. The variable "Vol" represents the volatility of inflation and is estimated using a family of ARCH and GARCH models.

4.1.3 Institutional Factors

Some literature suggests that institutional transparency and independence (e.g., central bank independence, see Cukierman, 1992) may affect inflation outcomes. We aim to proxy the impact of governance processes by incorporating variables connected to executive hiring and political rivalry. "Executive Recruitment Concept" (exrec) combines information about the regulation, competitiveness, and openness of executive recruitment. It pertains to the institutional factors that shape the process of selecting chief executives in a country's political system. This dimension helps in determining the overall level of democracy or autocracy in a given country by evaluating the process through which power is transferred or attained at the highest level of political leadership. The "Political Competition Concept" (polcomp) is a variable used to analyze and understand the level of political competition within a country's political system. It is a part of the POLITY IV PROJECT, which is a comprehensive data set that provides information on various political regime characteristics and transitions from the year 1800 to 2018.

Table 2: Indicator Data

Indicator Name	**Long Definition**	**Source**
Inflation, GDP deflator (annual %)	Inflation as measured by the annual growth rate of the GDP implicit deflator shows the rate of price change in the economy as a whole. The GDP implicit deflator is the ratio of GDP in current local currency to GDP in constant local currency.	World Bank national accounts data, and OECD National Accounts data files. "WDI Database Archives \ Data Catalog", n.d.

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[2] A free-falling currency regime can be defined as a monetary system in which the value of a nation's currency experiences rapid and uncontrolled depreciation due to market forces, without intervention from the country's central bank or government.

Table 2 – Continued

Indicator Name	Long Definition	Source
Trade (% of GDP)	Trade is the sum of exports and imports of goods and services measured as a share of gross domestic product.	World Bank national accounts data, and OECD National Accounts data files."WDI Database Archives \ Data Catalog", n.d.
Trade Globalisation, de facto (KOF)	The variable Trade Globalisation, de facto (KOF) represents a comprehensive measure of a country's trade activities and openness to the global economy. it can be broken in three different items: 1) Trade in goods Exports and imports of goods (% of GDP). 2) Trade in services Exports and imports of services (% of GDP). 3) Trade partner diversity Average of the Herfindahl-Hirschman market concentration index for exports and imports of goods (inverted).	The KOF Index of Globalisation. Gygli et al., 2019
General government final consumption expenditure (% of GDP)	General government final consumption expenditure (formerly general government consumption) includes all government current expenditures for purchases of goods and services (including compensation of employees). It also includes most expenditures on national defense and security but excludes government military expenditures that are part of government capital formation.	World Bank national accounts data, and OECD National Accounts data files. "WDI Database Archives \ Data Catalog", n.d.

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Table 2 – Continued

Indicator Name	**Long Definition**	**Source**
GDP growth (annual %)	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2015 prices, expressed in U.S. dollars.	World Bank national accounts data, and OECD National Accounts data files."WDI Database Archives \ Data Catalog", n.d.
Executive Recruitment Concept	Concept variable combines information about the Regulation of Chief Executive Recruitment, Competitiveness of Executive Recruitment and Openness of Executive Recruitment.	POLITY IV PROJECT Political Regime Characteristics and Transitions, 1800-2018 Dataset Users Manual. Marshall and Gurr, 2020
Political Competition Concept	Concept variable combines information about Regulation of Participation and The Competitiveness of Participation	POLITY IV PROJECT Political Regime Characteristics and Transitions, 1800-2018 Dataset Users Manual. Marshall and Gurr, 2020

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Table 2 – Continued

Indicator Name	Long Definition	Source
Foreign direct investment, net inflows (% of GDP)	Foreign direct investment are the net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. It is the sum of equity capital, reinvestment of earnings, other long-term capital, and short-term capital as shown in the balance of payments. This series shows net inflows (new investment inflows less disinvestment) in the reporting economy from foreign investors and is divided by GDP.	International Monetary Fund, International Financial Statistics and Balance of Payments databases, World Bank, International Debt Statistics, and World Bank and OECD GDP estimates. "WDI Database Archives \ Data Catalog", n.d.
Broad money growth (annual %)	Broad money is the sum of currency outside banks; demand deposits other than those of the central government; the time, savings, and foreign currency deposits of resident sectors other than the central government; bank and traveler's checks; and other securities such as certificates of deposit and commercial paper.	International Monetary Fund, International Financial Statistics, and data files. "WDI Database Archives \ Data Catalog", n.d.
Export diversification index	diversification across either products or trading partners.	International Monetary Fund. Papageorgiou et al., 2015 Henn et al., 2020
Exchange rate regime dummy	In this classification, we have created a dummy variable to identify "free regimes" by assigning a value of 1 to countries with Freely floating or Freely falling regimes, respectively, and a value of 0 to all other categories.	Ilzetzki, Ethan, Carmen M. Reinhart and Kenneth Rogoff (2021)Ilzetzki et al., 2017 Ilzetzki et al., 2021
gov_exp_m5, gdp_growth_m5	moving average for GDP growth and government expenditure for last five years.	created by authors.

Continued on next page

Table 2 – Continued

Indicator Name	Long Definition	Source
Inflation volatility	In this analysis, we have employed a family of ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models to estimate and forecast the volatility of inflation.	created by authors.

4.2 Model Specifications

In many cases, macro-panel data analysis often relies on estimators created for micro data sets, like the Arellano-Bond or Blundell-Bond estimators, designed for panels with a relatively small T compared to N. Considering the nature of macro-panel data, many characteristics like cross-section dependence error, heterogeneity in the slope coefficients across units, and the time series dimension, make these estimators become inadequate.

Our research is predicated on an expansive dataset and established continuity within inflation rates, which has led us to adopt the Dynamic Common Correlated Effects (DCCE) estimator, as proposed by Chudik and Pesaran (2015). The DCCE estimator presents an attractive option when both the cross-section and the time-series dimensions are substantially large.

The DCCE estimator has the added advantage of being robust to unknown types of cross-section dependence (CD) errors, which are anticipated due to the existence of common shocks and unobserved components. This is particularly pertinent in our context, given the heightened economic and financial integration over recent decades that has resulted in significant inter-dependencies among the cross-sectional units in our sample. The sample period (1970-2018) encompasses numerous macroeconomic and financial cycles, such as the oil shocks of the 1970s, the "Great Moderation" phase, and the secular decrease in inflation rates across all countries in our sample, as well as the shared shocks of the 2008 Recession. A failure to account for cross-sectional dependence can lead to severe biases, a problem that becomes more critical in dynamic panel settings, as explored by Phillips and Sul (2007). Also with over 100 countries over 50 years, there are likely to be global trends or unobserved common factors influencing both trade openness and inflation. The DCCE estimator has the advantage of approximating these unobserved common factors, enhancing the robustness of our analysis.

It is plausible to anticipate varying degrees of trade openness effects on inflation among different countries. The DCCE estimator allows for such heterogeneity in the slope coefficients across countries, ensuring an accurate and consistent estimation of the relationship between trade openness and inflation. To account for heterogeneity, we first calculate country-specific effects, which are subsequently amalgamated through a mean-group (MG) estimator to derive the average effects.

Our selection of a dynamic framework is inspired by the literature on inflation dynamics, which indicates significant persistence in inflation. Thus, in order to estimate the relationship between inflation rates and trade openness, after considering factors that impact inflation, our baseline specification is a heterogeneous dynamic panel model with a multifactor error structure.

$$\pi_{i,t} = \beta_i \text{trade\_openness}_{i,t} + \varphi_i \pi_{i,t-1} + \delta'_{0i} x_{i,t} + \delta'_{1i} x_{i,t-1} + u_{i,t} \tag{55}$$

$$u_{i,t} = \alpha_i + \lambda'_i f_t + e_{i,t}, \tag{56}$$

where $\pi_{i,t}$ is the inflation rate for country i in year t, $trade\_openness_{i,t}$ denotes the particular proxy being used to represent trade openness; $x_{i,t}$ is a k-dimensional vector of control variables as described in the previous subsection and assumed to be weakly exogenous; α_i accounts for time-invariant unobserved country-specific effects; f_t is a vector of latent common factors such as business cycles or exposure to global economic, political, or financial shocks – it has dimensions $m \times 1$ and is associated with specific country factor loadings λ'_i; finally, $e_{i,t}$ denotes idiosyncratic errors, which may exhibit correlation among different countries.

This model, with suitable restrictions on the parameters, subsumes several approaches employed in empirical practice, such as static and/or (partially) pooled panels. However, these frameworks could result in biased estimates, particularly in the presence of common unobserved factors, which is likely in our case. Consistent estimation is carried out using the DCCE estimator of Chudik and Pesaran, 2015, which approximates the unobserved common factors by supplementing the estimation equation with additional terms:

$$\pi_{it} = c_{i\pi} + \varphi_i \pi_{i,t-1} + \beta_{0i} \text{trade}_{it} + \beta_{1i} \text{trade}_{i,t-1} + \beta_{2i} x_{it} + \beta_{3i} x_{i,t-1} + \sum_{\ell=0}^{p_T} \delta'_{i\ell} \bar{z}_{t-\ell} + e_{yit}, \tag{57}$$

where $\bar{z}_t = \frac{1}{N} \sum_{i=1}^{N} z_{it} = (\bar{\pi}_t, \bar{x}_t, tr\bar{a}de_t)'$. We set p_T equal to the integer part of $T^{1/3}$, denoted as $p_T = \lfloor T^{1/3} \rfloor$, as recommended by Chudik and Pesaran, 2015: this gives the values of $p_T = 3$ for $40 <= T <= 50$.

We also computed bias-corrected versions of the CCEMG estimator using the half-panel jackknife discussed by Dhaene and Jochmans, 2015. Jackknife bias-corrected CCEMG estimators are constructed as:

$$\tilde{\pi}_{MG} = 2\hat{\pi}_{MG} - \frac{1}{2} \left(\hat{\pi}_{a,MG} + \hat{\pi}_{b,MG} \right), \tag{58}$$

where $\hat{\pi}_{a,MG}$ denotes the DCCE estimator computed from the first half of the available time period, namely over the period $t = 1, 2, \ldots, \left[\frac{T}{2}\right]$, where $\left[\frac{T}{2}\right]$ denotes the integer part of $\frac{T}{2}$, and $\hat{\pi}_{b,MG}$ is the CCEMG estimator computed using the observations over the period $t = \left[\frac{T}{2}\right] + 1, \left[\frac{T}{2}\right] + 2, \ldots, T$.

Furthermore, we will also examine an instrumental variable extension of the DCCE estimator that accommodates the potential of endogenous regressors, as well as the "half-panel jackknife" bias correction method.

5 Results

5.1 Preliminary Analysis

In this study, we begin with the unit root test to assess the stationarity of our time series data. The null hypothesis of the test is that the data have a unit root, meaning they are non-stationary.

Table 3: Unit root test for chosen variables

	Inf	trade	KOF	gdp_growth	gov_exp	exp_div	net_in	bro_mon_gr
Augmented Dickey-Fuller								
Lags								
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.001	0.000	0.000	0.002	0.000	0.000
3	0.000	0.000	0.000	0.000	0.000	0.006	0.000	0.000
Augmented Dickey-Fuller de-meaned								
Lags								
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.075	0.000	0.000	0.478	0.000	0.000
3	0.000	0.000	0.000	0.000	0.000	0.457	0.000	0.000
Phillips-Perron								
Lags								
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Phillips-Perron de-meaned								
Lags								
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
3	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000

Constant regression is used.

Table 3 presents the results of Augmented Dickey-Fuller (ADF), proposed by Dickey and Fuller, 1979 and Phillips-Perron (PP) unit root tests, proposed by Phillips and Perron, 1988, for 1, 2, and 3 lags respectively. The results are further split into those for the original series and the series where cross-sectional means have been subtracted (denoted with a de-meaned), an adjustment made to mitigate the impact of cross-sectional dependence.

Looking at the results, for almost all variables in all tests and at all lags, we can reject the null hypothesis of the presence of a unit root at a very high level of significance (p $<$ 0.001), indicating that these series are stationary. This is important, as it suggests that our data do not possess a time-dependent structure that could bias our subsequent analysis. The exceptions to this are the variables 'Export diversity' and 'KOF', which show some p-values greater than 0.001, suggesting that for these variables, we can reject the null hypothesis at these levels of significance.

Furthermore, we investigate the presence of cross-sectional correlation in our data, using the Pesaran, 2004 CD test. The Pesaran CD test is based on the average of pairwise correlation coefficients of the Ordinary Least Squares (OLS) residuals from the individual regressions in the panel. This test is applicable to various panel data models, including those with stationary and unit root dynamic heterogeneous panels. It is suitable for scenarios with short time dimensions (T) and large cross-sectional dimensions (N).

The CD test is correctly centred for fixed N and T, under the assumption that the underlying error processes are symmetrically distributed. This implies that the expected value of the test statistic under the null hypothesis (which posits no cross-sectional dependence) is zero.

The asymptotic distribution of a transformed version of the CD test statistic, denoted as z_N, follows a normal distribution with mean zero and variance one, i.e., $N(0,1)$. This holds true for any fixed $T > k+1$ (where k is the number of regressors) and as N approaches infinity. This distribution is predicated on certain assumptions, such as the cross-sectional independence of the pairwise correlation coefficients and the boundedness of their variances. In practical applications, a non-parametric estimation of the squared pairwise correlation coefficients is utilized. This estimation relies on scaled residuals. Commonly, it is expected that these estimated squared pairwise correlation coefficients will approximate $1/T$, thereby simplifying the computation of the test statistic.

The results are reported in Table 4. All p-values are 0.000, which indicates that we can reject the null hypothesis of no cross-sectional dependence for every variable listed. This implies that using estimators that do not take cross-sectional dependence into account may lead to erroneous inferences.

Table 4: Pesaran Test for cross-Section Correlation in the Data

	Inf	trade	KOF	gdp_growth	gov_exp	exp_div	net_in	bro_mon_gr
CD Test P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CD Test Statistic	154.2823	105.3287	108.7779	127.975	31.22018	15.11241	150.7963	73.99802

Nonetheless, in the next step we first report estimates using standard static panel estimators (pooled ordinary least squares [OLS] and fixed effects), using different sets of control variables. The model is built progressively across five different estimations (represented by columns 1 to 5). In column (1), only trade openness is used as an independent variable. In columns (2) to (4), macroeconomic variables are added to the model. These include GDP growth, government expenditure, exchange rate regime, net income, and broad money growth. We also included lagged variables and moving averages of some variables to estimate the effect of past periods in our models, such as inflation volatility, the 5-year moving average of government expenditure , the 5-year moving average of GDP growth, the lag of trade openness, and the lag of broad money growth. The last column (5) introduces institutional variables, the political competition concept, and the executive recruitment concept to control for regulatory and political differences in each country.

Table 6 reports estimates of the impact of various factors on inflation using pooled OLS estimations. Across all models, the coefficient for trade openness is negative, except in specification (1), where trade openness alone is considered, the relation being significant at the 0.001 level (as indicated by ***). When it comes to the CD test, all models fail to pass the test, suggesting significant cross-sectional correlation in residuals.

From the FE model, as shown in Table 7, the coefficient of the trade openness variable is, once again, consistently negative and statistically significant in the first three models. The magnitude of the coefficients is somewhat more negative in the FE model, suggesting that the effect of trade on inflation is more pronounced when we control for unobserved, time-invariant variables at the country level, but as with the OLS estimation none of the models pass the CD test.

In the next set of estimations, we add the first lag of inflation as an explanatory variable to account for inertia in inflation and help identify the impact of other explanatory variables on inflation more accurately by controlling for past inflation rates. The results of dynamic fixed effect estimations (DFE) are presented in Table 8. Looking at the results of both models, the estimates from the dynamic model suggest a positive and significant relation between the lag of inflation and inflation, as expected. Naturally, this relationship is not captured in the static model, which might lead to a specification error, as it misses a crucial element of the inflation process.

The Arellano-Bond estimator, as presented in Table 9, provides a contrast to previous specifications. Unlike previous models, where the trade openness variable showed a negative relationship with inflation, here it exhibits a positive coefficient from columns (2) to (5), although it remains statistically insignificant. This might suggest that the dynamic panel approach captures a different aspect of the trade-inflation relationship, or that potential endogeneity was indeed affecting earlier results. The lagged trade openness variable is mostly insignificant across the models it appears in.

5.2 Heterogenous Panel Estimations

In this section, we attempt to estimate the aforementioned relation with heterogeneous slopes models, namely using Mean Group Estimation (MG) as delineated by Pesaran and Smith, 1995, and the Common Correlated Estimation (CCE) as proposed by Chudik and Pesaran, 2015. Table 10 presents the results yielded by the MG method. One of the most salient findings from this analysis is that, when viewed across specifications, the coefficient for trade openness varies from a negative value in column (1) to a positive value in column (5). Intriguingly, trade openness is statistically significant at the p<0.05 level in both models (1) and (5). This highlights the possible non-linear relationship between trade and inflation, warranting deeper investigation. Also, the lag of the trade openness seems to fluctuate in sign across models, but remains statistically insignificant.

Utilizing the KOF index as a proxy for trade openness yields more consistent results (Table 11). The coefficients for contemporaneous and lagged KOF are negative and positive, respectively, and both statistically significant. However, for both proxies the results suggest the presence of strong cross-sectional dependence across all models, with the P-valueconsistently being 0, which indicates that the null hypothesis of no cross-sectional dependence is rejected in every case. The persistence of this cross-sectional correlation across all models, akin to the observations from all estimation methods used so far, emphasizes the need for caution when interpreting results, as it could signify omitted variables or common shocks affecting the countries in the panel.

The CCE estimations, delineated in Table 12 and 13, introduce another layer of depth to the analyses previously undertaken. As mentioned earlier, it is essential to include an adequate number of lags of cross-section averages to maintain the estimator's consistency. However, over-specifying lags can result in estimates that will not perform well in small samples. Thus, our approach incorporates up to $P_T = T^{\frac{1}{3}}$ lags for the three variables: inflation, trade openness, and GDP growth.

Considering the variable trade, it is notable that its direct influence on inflation is inconsistent across the models. Notably, in model (2) we observe a significant negative relationship at the $p < 0.05$ level. However, the subsequent model variants reflect an insignificant influence of trade openness on inflation. Delving deeper, the lagged trade variable (l_trade) manifests a more consistent and statistically significant positive impact on inflation, with its influence being statistically significant at the $p < 0.001$ level in models (2) and (3), and at the $p < 0.05$ level in models (4) and (5).

In contrast, when using the KOF trade index as the proxy of choice, the results are more consistent across models. The coefficient of KOF is negative and significant in models 2-5 and similar to the lag of trade, the coefficient for the lag of KOF shows a positive and significant relation in all models. This suggests that the effects of trade openness on inflation may not be immediate but rather exhibit a lagged, enduring impact.

Thus, the current stance on trade openness may not instantaneously dictate inflationary trends, but previous periods of openness could influence the present inflation rates.

Regarding the cross-sectional dependence (CD) test, a discernible trend is apparent. The CD test statistic values, which capture the magnitude of cross-sectional dependence, are progressively diminishing from model (1) to model (5) when using trade as the proxy, suggesting that the strength of the cross-sectional correlation is waning across the models. Moreover, it is noteworthy that once we progress to model (5), the P-valuerises to 0.146. This implies that at the $p < 0.1$ significance level, the null hypothesis of no cross-sectional dependence can no longer be firmly rejected for this model. While still relatively low, this P-valuein the model (5) is notably higher than in the preceding models, indicating a lessened degree of cross-sectional dependence. Similar to the previous findings with the trade proxy, the CD test results for the KOF proxy also suggest a high degree of cross-sectional dependence across models with no model with a P-valuehigher than 5%. This observation implies that regardless of the chosen proxy for trade openness, there exists a persistent concern related to potential common shocks or omitted factors influencing the countries in the panel when using CCE estimation.

Within the DCCE estimations, the multifaceted relationship between trade openness and inflation is further scrutinized. The findings continue to provide intriguing insights into this dynamic relationship. Looking closely, the direct 'trade' coefficient's influence on inflation seems to be inconsistent and mostly insignificant across the models. In contrast, once more the KOF trade index as a proxy portrays a more consistent negative relationship with inflation. Both lagged trade and lagged KOF show a predominantly positive relationship with inflation, suggesting past stances on trade openness can influence present inflation rates where the lagged KOF trade index (l_KOF) is also statistically significant.

We should recall that the KOF trade index is a multidimensional gauge, encapsulating information on actual flows (like imports and exports) and restrictions (like trade partner diversity). Its consistent negative relationship with inflation in these results underscores the nuanced insights this index offers compared to the basic trade metric. The use of the KOF index offers a more refined understanding, capturing not just the volume, but also the restrictive measures impacting trade.

Additionally, variables like GDP growth, government expenditure, and broad money growth show consistent and strong significance across all the models, indicating their importance in determining inflationary dynamics in the panel of countries. The negative sign for GDP growth and the positive sign for broad money growth are as expected, but the negative sign of the coefficient for government expenditure seems surprising, although we should keep in mind that the variable only represents the immediate effect of government expenditure. However, it is important to contextualize this by noting that the immediate effect might not capture the complete picture. This notion is supported by the positive and statistically significant relationship observed between inflation and the 'gov_exp_m5' variable, which represents the moving average of government expenditure over the past five years. This suggests that the broader, longer-term impact of government spending might diverge from its immediate effect, reinforcing the importance of considering both immediate and lagged influences when analyzing economic variables.

Concerning the cross-sectional dependence (CD) test, the DCCE estimations confirm the earlier observation: a diminishing trend of cross-sectional dependence from model (1) to model (5) for both proxies. With trade as the proxy, the P-valuereaches 0.478 for model (5), a marked increase from prior estimations. Also, when using KOF as a proxy, the p-values for model (5) is 0.232 indicating a reduced degree of cross-sectional dependence. This is crucial, because it suggests that in the DCCE model (5), cross-sectional dependence no longer a concern, and the null hypothesis of no cross-sectional dependence cannot be rejected.

In conclusion, the DCCE estimations further our understanding of the nuanced relationship between trade openness and inflation, emphasizing the lingering effects of past trade levels. Moreover, while cross-sectional dependence remains a concern across most models, the DCCE estimation provides a glimpse of a model where this issue is less pronounced.

5.3 Additional checks

To bolster the robustness and depth of our empirical findings in our study, we undertake a series of methodological enhancements and checks. Following this goal, we present three analyses:

5.3.1 Recursive Bias-Corrected DCCE

Given the complexities often inherent in dynamic panel data models, we apply a recursive bias correction proposed by So and Shin, 1999 to our DCCE estimations. This method emphasizes the demeaning of variables via the partial mean, ensuring it remains unaffected by prospective observations. Define the demeaned variables as:

$$\tilde{y}_{it} = y_{it} - \frac{1}{t-1} \sum_{s=1}^{t-1} y_{is}$$

and

$$\hat{\omega}_{it} = \omega_{it} - \frac{1}{t-1} \sum_{s=1}^{t-1} \omega_{is}$$

where $i = 1, 2, \ldots, N$ and $t = 2, 3, \ldots, T$, and $\omega_{it} = \begin{pmatrix} x'_{it} \\ g'_{it} \end{pmatrix}$. The bias-adjusted CCE mean group estimator is then computed based on the recursively demeaned variables $\tilde{y}_{it}$ and $\hat{\omega}_{it}$, utilizing $T-1$ available time periods, ranging from $t = 2$ to T.

The results are presented in Table 16. Starting with the variable 'trade', the recursive model suggests a negative coefficient of -0.227, although it is statistically insignificant with a large standard error. Shifting our focus to the 'KOF Index', the recursive model indicates a significant negative relationship with inflation, at the $p < 0.01$ level, with a coefficient of -0.457. Similarly, its lag, l_KOF, is positive and significant. The significance of the KOF Index, both in its contemporaneous and lagged forms, highlights the enduring impact of trade openness on inflation when this multidimensional proxy is utilized, resembling the results of the DCCE estimator. Regarding cross-section dependence, all models have p-values over 10% which means that they pass the CD test.

5.3.2 Jackknife bias correction Estimation

Recognized for its prowess in handling outlier sensitivities, the jackknife approach systematically omits one observation at a time from the sample set and recomputes the estimations. This iterative process ensures that our results are not overly reliant on any specific data point, bolstering the generalizability and reliability of our findings. In this study, we focus on the "half-panel jackknife" technique outlined by Dhaene and Jochmans, 2015 that caters for the $O(T^{-1})$ bias. The Jackknife bias-corrected CCEMG estimators are formulated as:

$$\hat{\pi}_{MG} = 2\bar{\pi}_{MG} - \frac{1}{2}(\hat{\pi}^a_{MG} + \hat{\pi}^b_{MG}),$$

where $\hat{\pi}^a_{MG}$ signifies the CCEMG estimator derived from the initial half of the designated timeframe, specifically spanning $t = 1, 2, \ldots, \lfloor \frac{T}{2} \rfloor$. Here, $\lfloor \frac{T}{2} \rfloor$ represents the integer value of $\frac{T}{2}$, and $\hat{\pi}^b_{MG}$ refers to the CCEMG estimators deduced from observations over the interval $t = \lfloor \frac{T}{2} \rfloor + 1, \lfloor \frac{T}{2} \rfloor + 2, \ldots, T$.

To effectively implement this method, it became necessary to refine our model by reducing the number of variables. This adjustment was primarily driven by a critical constraint: the span of the covered period is less than the total number of variables initially included. To address this issue and optimize our observational capacity, we selectively removed certain variables from the model. Specifically, we excluded 'net foreign investment' and 'export diversity', recognizing that these variables were restricting the scope of our observations. Additionally, 'GDP growth' was removed from the set of cross-sectional variables, streamlining the model further.

The outcomes of these modifications are detailed in Table 16. The results demonstrate that, while both models (incorporating trade and the KOF index) successfully passed the cross-sectional dependence CD test, the coefficients for the proxy variables exhibit a negative direction. However, it is important to underscore that none of these coefficients reached statistical significance. This outcome suggests that while the directional trends of the proxy variables are aligned with our theoretical expectations, their impact within the model does not achieve a level of statistical confidence to be deemed conclusively influential.

5.3.3 Instrumental Variables (IV) DCCE

One paramount extension merits our attention. The inflation dynamics literature, especially the prominent New Keynesian Phillips Curve, underscores the significance of expectations regarding future inflation in influencing present inflation. Empirical studies vindicate a "hybrid" rendition of the Phillips Curve, amalgamating both anticipated future inflation and historical inflation, as a compelling descriptor of inflationary tendencies (see Gali and Gertler, 2000, Mavroeidis et al., 2014, *inter alia*). Adapted to our case, this specification is represented as:

$$\pi_{i,t} = \beta_i \text{trade\_openness}_{i,t} + \phi_i^F E_t \pi_{i,t+1} + \phi_i^B \pi_{i,t-1} + \delta_i^0 x_{i,t} + \delta_i^1 x_{i,t-1} + u_{i,t}, \tag{59}$$

where E_t symbolizes the (conditional) expectations formed at time t. Given the lack of inflation expectations measures for all countries in our dataset, the standard convention is to replace the term $E_t \pi_{i,t+1}$ with actual observed values. This substitution, however, engenders potential endogeneity issues through an appended expectational error. Thus, to adequately gauge this relationship, an instrumental variable approach becomes indispensable. Adapting the DCCE estimator of Chudik and Pesaran, 2015 to an IV/GMM framework is unproblematic, as discussed in Neal, 2015.

Looking at the results for the 'trade' variable in Table 16, the IV model suggests an insignificant negative relation of -0.083. However, when examining the lag of the trade variable (l_trade), again none of the coefficients are statistically significant under 5 percent. Considering the KOF index yields similar results: when using the IV estimator, both coefficients for contemporaneous and lagged are negative, but not statistically significant. Turning our attention to the cross-sectional dependence CD test, the results further echo our prior findings in DCCE models. For instance, the p-values are above 0.1 for all models, suggesting a reduced level of cross-sectional dependence in the models.

5.3.4 Testing for Non-Linearity

We assess potential non-linearities in the relationships by means of a RESET test. Thus, the squared and cubed form of the fitted values were added to the model and then subsequently, a Wald test was conducted to test the joint hypothesis that the coefficients of these non-linear terms are equal to zero. Results are presented in Table 5, showing a Chi-square statistic of 5.29 for Trade and 4.68 for the KOF Index, with p-values of 0.071 and 0.096, respectively. The p-values being greater than the conventional significance level of 5% (0.05) for both Trade and the KOF Index suggest that the evidence supporting a non-linear model is relatively weak. In simpler terms, while the model hints at some level of non-linearity, this indication is not strong enough to decisively reject the null hypothesis of linearity at the 5% significance level. Therefore, caution should be exercised before concluding the presence of a non-linear relationship in the data.

Table 5: Wald Test results

	Trade	KOF Index
χ^2	5.29	4.68
P-value	0.071	0.096

Null hypothesis: The relationship between the variables is linear.

5.3.5 Analysis of the effect of trade openness on inflation by country income levels

It may be the case that the relationship between inflation and trade openness is distinct for different levels of income across countries. Using the World Bank definitions for high, upper-middle, lower-middle, and low income levels, the impact of trade openness on inflation is estimated in Table 17 for different country groups.[3]

Starting with the variable 'trade', its coefficient is positive for high-income countries (0.037) and upper-middle-income countries (0.084), although not statistically significant, suggesting a mild inflationary pressure associated with trade openness in these groups. Conversely, in lower-middle-income countries, trade openness seems to have a negligible negative effect (-0.040), whereas in low-income countries, the impact is significantly negative and more substantial (-0.495**), indicating a potential deflationary influence of trade openness.

The lagged trade variable ('l_trade') shows a more pronounced positive effect in upper middle-income and low-income countries (0.281 and 0.588***, respectively), hinting at a delayed inflationary response to trade openness in these groups. High and lower

[3] The full list of countries is presented in Appendix B.

middle-income countries show smaller positive coefficients (0.015 and 0.107, respectively), suggesting a more muted delayed effect.

The KOF Globalization Index (KOF) exhibits interesting dynamics. In the immediate term, higher KOF index values are associated with lower inflation in upper middle-income countries (-0.538*), but this relationship is not significant in other groups. However, the lagged KOF index ('l_KOF') reveals a substantial positive association with inflation in upper middle and low income countries (0.864** and 0.644** respectively), indicating a more pronounced delayed inflationary impact in these groups. In other income groups, the KOF coefficient is not significant.

It is important to note the presence of cross-sectional dependence in the data, as indicated by the CD test statistics, especially in high-income countries (4.100) and to a lesser extent in low-income countries (2.391). This suggests that inflationary trends in these countries may be exposed to cross-sectional dependence problems.

In summary, the table reveals that the impact of trade openness on inflation varies significantly across different income groups of countries. In high and upper middle-income countries, the effect is generally mild and not statistically significant in the immediate term, but shows a delayed inflationary impact. In contrast, in the lower middle and particularly in low-income countries, trade openness appears to have a more immediate and substantial deflationary effect, but this reverses to a significant inflationary impact over time. This nuanced understanding underscores the complexity of the trade-inflation nexus and the importance of considering income levels and temporal dynamics in policy analysis.

6 Conclusion

Our study aimed at disentangling the intricate relationship between trade openness and inflation, particularly probing into the non-linear dynamics that might exist. The common narrative suggesting a straightforward negative correlation between trade openness and inflation is challenged by our results. Central to our hypothesis was the notion that many previous studies may have overlooked the importance of cross-sectional dependence in panel data, thereby possibly misinterpreting the observed relationship.

Our investigation relied upon a spectrum of economic, political, and financial indicators, as detailed in Table 2. For robustness considerations, countries with scant data, namely fewer than 20 observations, were eliminated, and data points indicating inflation rates surging above 500% annually were deemed outliers and therefore excluded.

Two key proxies for trade openness were employed: the basic "trade" metric, calculated as the sum of imports and exports divided by GDP, and the more nuanced KOF trade openness index. Both measures provided rich insights, though the KOF index seemed particularly adept at capturing the multifaceted nature of trade openness.

Initial investigations with standard static panel estimators, while providing insightful glimpses, raised serious concerns about cross-sectional dependence. This observation was consistent, be it pooled OLS, fixed effects, or dynamic fixed effect models. Moreover, the dynamism of trade's influence on inflation, as unveiled by these models, hints at a more complex underlying relationship than previously assumed. Trade's direct effect seemed to waver in consistency, while its lagged effect maintained a more consistent tone, indicating past levels of trade openness may influence current inflation trajectories. Such fluctuations underscore the non-linear and intricate nature of the relationship.

The persistent observation of cross-sectional dependence across models, regardless of the estimator or proxy for trade openness, was particularly noteworthy. This suggested potential common shocks or omitted factors influencing the panel countries, a crucial observation, reiterating the importance of accounting for cross-sectional dependence when working with panel data in such contexts.

Considering heterogeneous panel estimations, our use of the Mean Group (MG) estimator highlighted an intriguing finding: the relationship between trade openness and inflation is potentially non-linear, given the fluctuating coefficient signs across models. The strong and consistent cross-sectional dependence in all models, irrespective of the chosen proxy, indicates that the problem is persisting.

The Common Correlated Estimation (CCE) further enhanced our insights. A particularly significant observation emerged from the cross-sectional dependence (CD) test in our DCCE estimations. The declining trend of cross-sectional dependence from model (1) to model (5), for both trade proxies, suggests that by the time we reach model (5), the correlation between sections is waning. This is vital as it suggests that, especially in the DCCE model (5), the results are not unduly influenced by common shocks or omitted variables. There was no definitive answer to the question of whether inflation and trade openness were related in the absence of cross-sectional dependence, the traditional trade openness proxy was not statistically significant, and even though the contemporaneous coefficient for the KOF index was negative and statistically significant, the positive lagged coefficient was positive and negated its effect.

For further checks, we used recursive bias correction and IV models that corroborated the complexity in the trade-inflation relationship. The significant impact of the KOF Index, especially when analyzed using the recursive model, attested to the merits of using multidimensional proxies in compare to share of trade in GDP. These additional checks resonated with the core of our research – the relationship between trade openness and inflation is multifaceted, influenced by various direct and lagged variables, and shaped by underlying common shocks or influences.

In sum, our investigation reveals that the link between trade openness and inflation is far from straightforward. Relying on simplistic metrics or not accounting for critical factors like cross-sectional dependence can lead to misinterpretations. Our results highlight the need for caution, meticulous analysis, and the use of robust proxies when investigating such economic relationships. The world of trade and its impact on inflation is intricate, and our study seeks to shed light on its complex interplay, providing a more holistic understanding. Future research should continue in this direction, ensuring that all particularities are considered for policy implications and practical applications.

Table 6: Static Homogeneous Panel: Pooled OLS Estimations

Inflation as dependent variable

	(1)	(2)	(3)	(4)	(5)
trade	-0.067***	-0.084	-0.086	-0.067	-0.067
	(0.006)	(0.044)	(0.048)	(0.046)	(0.052)
l_trade		0.064	0.092	0.070	0.072
		(0.045)	(0.048)	(0.045)	(0.051)
gdp_growth		-0.573***	-0.562***	-0.452***	-0.470***
		(0.095)	(0.105)	(0.102)	(0.112)
gov_exp		-0.125	-0.182*	-1.414***	-1.490***
		(0.073)	(0.076)	(0.237)	(0.263)
bro_mon_gr		0.574***	0.498***	0.446***	0.444***
		(0.111)	(0.113)	(0.111)	(0.113)
Ex_re			21.427***	18.723***	18.575***
			(3.321)	(2.804)	(2.825)
net_in			-0.156**	-0.134*	-0.104
			(0.055)	(0.052)	(0.061)
exp_div			0.726**	0.537*	0.395
			(0.231)	(0.223)	(0.256)
Vol				0.000	-0.000
				(0.000)	(0.000)
gov_exp_m5				1.354***	1.445***
				(0.241)	(0.268)
gdp_growth_m5				-0.323**	-0.378**
				(0.125)	(0.136)
l_bro_mon_gr				0.040***	0.040***
				(0.009)	(0.009)
exrec					0.621***
					(0.165)
polcomp					-0.602***
					(0.165)
N	8129	6116	5090	4878	4318
adj. R^2	0.012	0.453	0.487	0.549	0.548
CD Test P-value	0.000	0.000	0.000	0.000	0.000
CD Test Statistic	116.599	61.225	43.715	42.225	36.683

Standard errors in parentheses

The CD Test P-value and Test Statistic represent the Pesaran Cd test results and are calculated to test the null hypothesis of no cross-sectional dependence in the panel data.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Static Homogeneous Panel: Fixed Effects Estimations

Inflation as dependent variable

	(1)	(2)	(3)	(4)	(5)
trade	-0.077*	-0.076*	-0.089*	-0.070	-0.072
	(0.036)	(0.036)	(0.039)	(0.041)	(0.047)
l_trade		0.051	0.078	0.060	0.059
		(0.044)	(0.041)	(0.043)	(0.050)
gdp_growth		-0.538***	-0.525***	-0.431***	-0.441***
		(0.103)	(0.109)	(0.092)	(0.101)
gov_exp		-0.306*	-0.439***	-1.426***	-1.486***
		(0.155)	(0.118)	(0.306)	(0.339)
bro_mon_gr		0.529***	0.444***	0.398***	0.397***
		(0.107)	(0.105)	(0.114)	(0.115)
Ex_re			26.589***	23.494***	23.524***
			(4.927)	(4.397)	(4.502)
net_in			-0.145	-0.129	-0.119
			(0.080)	(0.070)	(0.083)
exp_div			0.800	0.292	0.183
			(0.510)	(0.477)	(0.523)
Vol				0.000*	0.000
				(0.000)	(0.000)
gov_exp_m5				1.335***	1.383***
				(0.349)	(0.381)
gdp_growth_m5				-0.325*	-0.358*
				(0.150)	(0.166)
l_bro_mon_gr				0.040***	0.040***
				(0.009)	(0.009)
exrec					0.550
					(0.333)
polcomp					-0.540
					(0.341)
N	8129	6116	5090	4878	4318
adj. R^2	0.004	0.387	0.425	0.500	0.502
CD Test P-value	0.000	0.000	0.000	0.000	0.000
CD Test Statistic	112.396	62.710	44.523	43.756	37.240

Standard errors in parentheses

The CD Test P-value and Test Statistic represent the Pesaran Cd test results and are calculated to test the null hypothesis of no cross-sectional dependence in the panel data.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Homogeneous Panel: Dynamic Fixed Effects Estimations

Inflation as dependent variable

	(1)	(2)	(3)	(4)	(5)
Inf_l	0.024***	0.015***	0.014***	0.001	0.001
	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)
trade	-0.069*	-0.075*	-0.088*	-0.071	-0.072
	(0.031)	(0.035)	(0.037)	(0.041)	(0.047)
l_trade		0.050	0.077	0.061	0.059
		(0.042)	(0.040)	(0.043)	(0.050)
gdp_growth		-0.510***	-0.490***	-0.433***	-0.443***
		(0.103)	(0.111)	(0.093)	(0.102)
gov_exp		-0.310*	-0.411***	-1.431***	-1.491***
		(0.139)	(0.113)	(0.308)	(0.341)
bro_mon_gr		0.491***	0.408***	0.398***	0.397***
		(0.112)	(0.111)	(0.114)	(0.115)
Ex_re			25.926***	23.508***	23.541***
			(4.782)	(4.425)	(4.533)
net_in			-0.136	-0.126	-0.118
			(0.076)	(0.070)	(0.083)
exp_div			0.711	0.285	0.184
			(0.502)	(0.479)	(0.527)
Vol				0.000*	0.000
				(0.000)	(0.000)
gov_exp_m5				1.331***	1.379***
				(0.350)	(0.382)
gdp_growth_m5				-0.332*	-0.365*
				(0.152)	(0.168)
l_bro_mon_gr				0.038**	0.038**
				(0.013)	(0.013)
exrec					0.556
					(0.335)
polcomp					-0.544
					(0.342)
N	7969	6101	5079	4870	4313
adj. R^2	0.093	0.432	0.473	0.500	0.502
CD Test P-value	0.000	0.000	0.000	0.000	0.000
CD Test Statistic	110.435	64.485	47.003	43.912	37.293

Standard errors in parentheses

The CD Test P-value and Test Statistic represent the Pesaran Cd test results and are calculated to test the null hypothesis of no cross-sectional dependence in the panel data.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Dynamic Homogeneous Panel: System GMM Estimations

Inflation as dependent variable					
	(1)	(2)	(3)	(4)	(5)
l_Inf	0.167*	-0.012	-0.009	-0.131***	-0.135***
	(0.072)	(0.019)	(0.019)	(0.024)	(0.023)
trade	-0.354	0.067	0.162	0.185	0.177
	(0.300)	(0.195)	(0.274)	(0.263)	(0.266)
l_trade		0.069	-0.043	-0.070	-0.052
		(0.155)	(0.250)	(0.248)	(0.245)
gdp_growth		-1.077***	-1.464***	-0.685	-0.469
		(0.249)	(0.384)	(0.527)	(0.589)
gov_exp		-0.926	-0.445	-5.667*	-6.266*
		(1.013)	(0.745)	(2.761)	(3.058)
bro_mon_gr		2.228***	2.239***	2.142***	2.137***
		(0.634)	(0.643)	(0.621)	(0.614)
Ex_re			-43.319	-43.810	-38.810
			(36.424)	(32.864)	(29.324)
net_in			-0.264	-0.047	-0.192
			(0.212)	(0.126)	(0.125)
exp_div			3.744	3.993	3.103
			(3.262)	(2.682)	(2.639)
Vol				1.72e-12	3.59e-6
				(0.000)	(0.000)
gov_exp_m5				5.898*	6.626
				(2.966)	(3.408)
gdp_growth_m5				-3.219*	-2.918*
				(1.468)	(1.387)
l_bro_mon_gr				0.316***	0.320***
				(0.052)	(0.053)
exrec					-5.625*
					(2.708)
polcomp					4.309*
					(2.013)
N	7969	6101	5079	4870	4313
CD Test P-value	0.000	0.000	0.000	0.000	0.000
CD Test Statistic	47.407	29.717	17.227	17.534	14.437

p-values in parentheses
The CD Test P-value and Test Statistic represent the Pesaran Cd test results and are calculated to test the null hypothesis of no cross-sectional dependence in the panel data.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Static Heterogeneous Panel: Mean Group Estimations

Inflation as dependent variable					
	(1)	(2)	(3)	(4)	(5)
trade	-0.146*	-0.0119	0.0380	0.105	0.156*
	(0.0581)	(0.0509)	(0.0592)	(0.0644)	(0.0772)
l_trade		0.0327	0.0667	-0.00618	-0.0426
		(0.0507)	(0.0642)	(0.0703)	(0.0801)
gdp_growth		-0.635***	-0.616***	-0.427***	-0.445***
		(0.105)	(0.117)	(0.0890)	(0.101)
gov_exp		-0.864***	-1.030***	-1.498***	-1.523***
		(0.169)	(0.210)	(0.310)	(0.333)
bro_mon_gr		0.355***	0.293***	0.201***	0.209***
		(0.0361)	(0.0380)	(0.0304)	(0.0342)
Ex_re			8.576***	3.239*	5.529**
			(2.235)	(1.300)	(2.009)
net_in			-0.564*	-0.0639	-0.169
			(0.230)	(0.166)	(0.181)
exp_div			0.515	-4.634	-5.900
			(2.508)	(3.002)	(3.507)
Vol				0.320*	0.322
				(0.159)	(0.209)
gov_exp_m5				1.013**	1.158**
				(0.331)	(0.360)
gdp_growth_m5				-0.142	-0.248
				(0.193)	(0.224)
l_bro_mon_gr				0.0770***	0.0686**
				(0.0209)	(0.0246)
exrec					1.198
					(0.868)
polcomp					-1.051
					(0.978)
N	8129	6116	5090	4878	4318
CD Test P-value	0.000	0.000	0.000	0.000	0.000
CD Test Statistic	93.833	41.883	28.336	19.695	17.462

Standard errors in parentheses

The CD Test P-value and Test Statistic represent the Pesaran Cd test results and are calculated to test the null hypothesis of no cross-sectional dependence in the panel data.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Static Heterogeneous Panel: Mean Group Estimations (KOF Index)

Inflation as dependent variable

	(1)	(2)	(3)	(4)	(5)
KOF	-0.080*	-0.187*	-0.205	-0.101	-0.077
	(0.034)	(0.085)	(0.117)	(0.110)	(0.126)
l_KOF		0.178*	0.247*	0.239*	0.199
		(0.087)	(0.117)	(0.101)	(0.113)
gdp_growth		-0.590***	-0.537***	-0.399***	-0.400***
		(0.108)	(0.108)	(0.090)	(0.089)
gov_exp		-0.744***	-0.957***	-1.181***	-1.319***
		(0.174)	(0.228)	(0.322)	(0.315)
bro_mon_gr		0.352***	0.295***	0.217***	0.215***
		(0.034)	(0.035)	(0.029)	(0.033)
Ex_re			9.010***	3.727*	6.549***
			(2.395)	(1.548)	(1.893)
net_in			-0.485*	-0.126	-0.295
			(0.241)	(0.188)	(0.203)
exp_div			1.635	-1.648	-3.825
			(2.012)	(1.679)	(2.182)
Vol				0.402**	0.433**
				(0.131)	(0.158)
gov_exp_m5				1.085***	1.170***
				(0.315)	(0.319)
gdp_growth_m5				0.009	-0.163
				(0.220)	(0.253)
l_bro_mon_gr				0.084***	0.073***
				(0.020)	(0.021)
exrec					0.484
					(0.520)
polcomp					-0.313
					(1.086)
N	8044	6106	5075	4866	4313
CD Test P-value	0.000	0.000	0.000	0.000	0.000
CD Test Statistic	86.126	44.188	31.053	21.172	20.458

Standard errors in parentheses
The CD Test P-value and Test Statistic represent the Pesaran Cd test results and are calculated to test the null hypothesis of no cross-sectional dependence in the panel data.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Static Heterogeneous Panel: CCE Estimations

Inflation as dependent variable					
	(1)	(2)	(3)	(4)	(5)
trade	0.074	-0.120*	-0.115	0.031	-0.046
	(0.052)	(0.057)	(0.078)	(0.078)	(0.100)
l_trade		0.235***	0.250***	0.164*	0.212*
		(0.057)	(0.068)	(0.081)	(0.101)
gdp_growth		-0.801***	-0.649***	-0.559***	-0.606***
		(0.152)	(0.130)	(0.090)	(0.129)
gov_exp		-0.761***	-1.078***	-1.551***	-1.795***
		(0.218)	(0.319)	(0.340)	(0.388)
bro_mon_gr		0.233***	0.207***	0.160***	0.191***
		(0.031)	(0.035)	(0.031)	(0.037)
Ex_re			3.156	3.737	4.792
			(1.809)	(3.398)	(3.615)
net_in			-0.351	0.120	-0.000
			(0.270)	(0.294)	(0.319)
exp_div			2.192	-2.149	-3.420
			(3.106)	(3.121)	(3.851)
Vol				0.419	0.483
				(0.217)	(0.313)
gov_exp_m5				1.483***	1.310**
				(0.386)	(0.468)
gdp_growth_m5				-0.114	-0.215
				(0.234)	(0.281)
l_bro_mon_gr				0.051	0.033
				(0.029)	(0.030)
exrec					-1.118
					(1.424)
polcomp					2.606*
					(1.289)
_cons	3.849	13.781	10.236	-1.104	26.713
	(13.119)	(12.462)	(13.985)	(16.222)	(30.541)
N	7808	5960	4545	4269	3568
CD Test P-value	0.000	0.000	0.000	0.012	0.146
CD Test Statistic	21.393	7.409	3.754	2.503	1.452

Standard errors in parentheses
The CD Test P-value and Test Statistic represent the Pesaran Cd test results and are calculated to test the null hypothesis of no cross-sectional dependence in the panel data.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Static Heterogeneous Panel: CCE Estimations (KOF Index)

Inflation as dependent variable					
	(1)	(2)	(3)	(4)	(5)
KOF	0.038	-0.314***	-0.372***	-0.346**	-0.373*
	(0.093)	(0.090)	(0.089)	(0.130)	(0.147)
l_KOF		0.382***	0.578***	0.406***	0.559***
		(0.094)	(0.115)	(0.103)	(0.132)
gdp_growth		-0.759***	-0.568***	-0.543***	-0.569***
		(0.119)	(0.123)	(0.083)	(0.103)
gov_exp		-0.988***	-1.041**	-1.493***	-1.587***
		(0.217)	(0.322)	(0.369)	(0.338)
bro_mon_gr		0.211***	0.197***	0.172***	0.185***
		(0.032)	(0.033)	(0.028)	(0.036)
Ex_re			5.807**	5.909	5.994
			(1.901)	(3.024)	(4.059)
net_in			-0.581*	-0.177	-0.410
			(0.270)	(0.333)	(0.334)
exp_div			1.272	-1.775	-0.667
			(1.899)	(2.394)	(2.380)
Vol				0.492*	0.643*
				(0.191)	(0.292)
gov_exp_m5				1.249**	1.041*
				(0.400)	(0.500)
gdp_growth_m5				0.217	-0.199
				(0.318)	(0.340)
l_bro_mon_gr				0.072**	0.056*
				(0.025)	(0.025)
exrec					-1.103
					(1.462)
polcomp					2.084
					(1.199)
N	7730	5952	4532	4230	3533
CD Test P-value	0.000	0.000	0.000	0.008	0.007
CD Test Statistic	20.029	8.866	4.342	2.640	2.674

Standard errors in parentheses

The CD Test P-value and Test Statistic represent the Pesaran Cd test results and are calculated to test the null hypothesis of no cross-sectional dependence in the panel data.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Dynamic Heterogeneous Panel: CCE Estimations

Inflation as dependent variable					
	(1)	(2)	(3)	(4)	(5)
l_Inf	0.214***	0.075**	0.019	0.030	0.020
	(0.033)	(0.026)	(0.029)	(0.070)	(0.062)
trade	0.058	-0.064	-0.058	0.006	-0.052
	(0.042)	(0.052)	(0.065)	(0.064)	(0.094)
l_trade		0.186***	0.219**	0.164*	0.180
		(0.056)	(0.075)	(0.082)	(0.100)
gdp_growth		-0.915***	-0.654***	-0.595***	-0.657***
		(0.196)	(0.122)	(0.108)	(0.143)
gov_exp		-0.697**	-0.879**	-1.616***	-1.823***
		(0.234)	(0.287)	(0.388)	(0.413)
bro_mon_gr		0.207***	0.186***	0.158***	0.196***
		(0.035)	(0.035)	(0.033)	(0.038)
Ex_re			2.875	1.342	1.296
			(1.901)	(3.452)	(3.535)
net_in			-0.024	0.274	-0.015
			(0.247)	(0.306)	(0.308)
exp_div			-0.226	-0.726	-2.270
			(3.012)	(2.469)	(3.073)
Vol				0.450	0.546
				(0.243)	(0.345)
gov_exp_m5				1.487***	1.500**
				(0.429)	(0.491)
gdp_growth_m5				-0.159	-0.263
				(0.259)	(0.332)
l_bro_mon_gr				0.056*	0.060*
				(0.026)	(0.028)
exrec					-1.577
					(1.529)
polcomp					1.733
					(0.998)
N	7756	5907	4513	4210	3565
CD Test P-value	0.000	0.000	0.005	0.021	0.478
CD Test Statistic	16.611	6.063	2.815	2.314	0.709

Standard errors in parentheses
The CD Test P-value and Test Statistic represent the Pesaran Cd test results and are calculated to test the null hypothesis of no cross-sectional dependence in the panel data.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Dynamic Heterogeneous Panel: CCE Estimations (KOF Index)

Inflation as dependent variable					
	(1)	(2)	(3)	(4)	(5)
l_Inf	0.192***	0.063*	0.051	0.001	-0.057
	(0.021)	(0.032)	(0.027)	(0.055)	(0.064)
KOF	0.073	-0.195*	-0.374***	-0.302*	-0.317*
	(0.070)	(0.095)	(0.096)	(0.130)	(0.157)
l_KOF		0.374***	0.619***	0.346**	0.498***
		(0.084)	(0.118)	(0.107)	(0.134)
gdp_growth		-0.706***	-0.573***	-0.534***	-0.592***
		(0.130)	(0.116)	(0.101)	(0.122)
gov_exp		-0.810***	-0.951**	-1.503***	-1.523***
		(0.205)	(0.314)	(0.384)	(0.335)
bro_mon_gr		0.198***	0.213***	0.158***	0.186***
		(0.049)	(0.042)	(0.030)	(0.040)
Ex_re			5.800**	3.572	1.892
			(2.004)	(2.063)	(3.632)
net_in			-0.486	-0.146	-0.532
			(0.254)	(0.292)	(0.322)
exp_div			1.364	-1.211	-0.672
			(1.986)	(2.449)	(2.367)
Vol				0.548*	0.650*
				(0.213)	(0.325)
gov_exp_m5				1.291**	0.923
				(0.433)	(0.548)
gdp_growth_m5				0.143	-0.579
				(0.308)	(0.472)
l_bro_mon_gr				0.084***	0.082**
				(0.023)	(0.028)
exrec					-2.322
					(1.801)
polcomp					2.355
					(1.328)
N	7679	5916	4499	4197	3529
CD Test P-value	0.000	0.000	0.013	0.027	0.232
CD Test Statistic	18.052	8.810	2.481	2.206	1.194

Standard errors in parentheses

The CD Test P-value and Test Statistic represent the Pesaran Cd test results and are calculated to test the null hypothesis of no cross-sectional dependence in the panel data.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Additional checks

Inflation as dependent variable						
		Trade			KOF Index	
	(Recursive)	(Jackknife)	(IV)	(Recursive)	(Jackknife)	(IV)
f_Inf			-1.880			0.173
			(2.473)			(0.298)
l_Inf	-0.116	-0.040	-0.735	-0.184	-0.540	0.079
	(0.082)	(0.266)	(1.048)	(0.085)	(0.321)	(0.144)
trade	-0.227	-0.210	-0.083			
	(0.195)	(0.399)	(1.061)			
l_trade	0.016	0.421	1.098			
	(0.149)	(0.293)	(0.983)			
KOF				-0.457	-0.709	-0.338
				(0.161)	(0.339)	(0.358)
l_KOF				0.543	0.570	-0.044
				(0.200)	(0.541)	(0.359)
gov_exp	-1.716	-2.248	-4.066	-1.738	-1.817	-2.072
	(0.348)	(1.269)	(8.722)	(0.392)	(0.922)	(0.653)
gdp_growth	-0.533	-1.258	-0.791	-0.583	-1.201**	-1.059
	(0.186)	(0.404)	(3.357)	(0.161)	(0.450)	(0.444)
bro_mon_gr	0.151	0.377	-0.414	0.150	0.362	0.147
	(0.032)	(0.155)	(0.746)	(0.029)	(0.227)	(0.083)
Ex_re	12.185	-0.030	-36.512	5.775	-4.680	4.121
	(6.750)	(9.223)	(77.456)	(4.485)	(5.363)	(2.984)
net_in	0.446		1.743	-0.295		-1.413
	(0.387)		(3.289)	(0.349)		(0.763)
exp_div	-0.275		-52.630	-3.281		-9.096
	(4.636)		(33.581)	(3.280)		(6.410)
Vol	0.639	0.470	-1.154	0.836**	0.754	0.817
	(0.320)	(0.701)	(3.812)	(0.235)	(0.568)	(0.618)
gov_exp_m5	0.400	2.553	7.637	1.297	0.811	-1.077
	(0.528)	(2.910)	(14.640)	(0.561)	(2.023)	(1.176)
gdp_growth_m5	0.356	0.111	-3.656	0.024	-1.118	-0.303
	(0.454)	(1.133)	(6.530)	(0.453)	(1.089)	(0.858)
l_bro_mon_gr	0.042	0.177	-0.566	0.077*	0.033	0.068
	(0.031)	(0.133)	(0.694)	(0.032)	(0.103)	(0.051)
exrec	4.333	-0.030	49.939	10.376	-4.680	2.846
	(5.208)	(9.223)	(55.398)	(6.245)	(5.363)	(2.379)
polcomp	0.828	8.447	-43.412	1.078	5.034	-2.908
	(1.952)	(14.575)	(40.430)	(1.958)	(5.208)	(3.218)
N	3459	3565	3528	3427	3529	3492
CD Test P-value	0.369	0.373	0.688	0.141	0.178	0.906
CD Test Statistic	-0.896	0.890	0.401	1.470	1.344	0.117

Standard errors in parentheses
The CD Test P-value and Test Statistic represent the Pesaran Cd test results and are calculated to test the null-hypothesis of no cross-sectional dependence in the panel data.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Country groups by income

	(High)	(Upper middle)	(Lower middle)	(Low)	(High)	(Upper middle)	(Lower middle)	(Low)
l_Inf	-0.023	0.263	-0.026	-0.213	0.037	0.083	-0.179	-0.215
	(0.089)	(0.160)	(0.064)	(0.190)	(0.101)	(0.146)	(0.107)	(0.182)
trade	0.037	0.084	-0.040	-0.495**				
	(0.233)	(0.210)	(0.109)	(0.171)				
l_trade	0.015	0.281	0.107	0.588***				
	(0.182)	(0.247)	(0.141)	(0.175)				
KOF					-0.232	-0.538*	-0.350	-0.160
					(0.423)	(0.271)	(0.207)	(0.374)
l_KOF					0.389	0.864**	0.283	0.644**
					(0.257)	(0.317)	(0.210)	(0.245)
gov_exp	-1.844*	-2.125***	-1.470*	-2.033	-1.461	-2.728***	-0.533	-1.265*
	(0.862)	(0.635)	(0.678)	(1.424)	(0.786)	(0.643)	(0.558)	(0.549)
gdp_growth	-0.439	-0.760**	-0.768***	-0.544	-0.462*	-0.712**	-0.755***	-0.254
	(0.327)	(0.288)	(0.227)	(0.342)	(0.224)	(0.274)	(0.192)	(0.329)
bro_mon_gr	0.144*	0.325***	0.142	0.169**	0.077	0.313***	0.184*	0.164
	(0.067)	(0.076)	(0.084)	(0.064)	(0.059)	(0.067)	(0.094)	(0.092)
Ex_re	9.490	4.009	-6.341	-0.645	8.768	4.109	-5.079	0.914
	(5.788)	(3.919)	(9.378)	(6.112)	(6.019)	(3.309)	(10.487)	(3.771)
net_in	-0.237	-0.662	-0.110	1.486	-0.401	-1.204*	-0.340	-0.089
	(0.225)	(0.404)	(0.588)	(1.290)	(0.435)	(0.508)	(0.664)	(1.125)
exp_div	-6.297	-0.859	-1.428	1.360	0.191	0.952	-0.252	-4.901
	(9.167)	(3.509)	(5.287)	(4.712)	(3.711)	(3.824)	(5.852)	(5.302)
Vol	0.598***	0.639	-0.109	1.414**	0.648*	0.550	0.205	1.537***
	(0.166)	(0.584)	(0.973)	(0.512)	(0.291)	(0.473)	(0.951)	(0.466)
gov_exp_m5	0.518	2.448**	1.356	1.409	-0.426	2.808***	-0.138	1.720
	(0.759)	(0.826)	(1.221)	(0.769)	(1.277)	(0.836)	(1.076)	(0.955)
gdp_growth_m5	-0.580	0.347	-0.037	-1.062	-0.547	0.034	-0.356	-1.815
	(0.429)	(0.586)	(0.749)	(0.920)	(0.700)	(0.870)	(1.103)	(1.082)
l_bro_mon_gr	-0.030	0.159***	0.022	0.088	-0.001	0.160***	0.047	0.138*
	(0.052)	(0.040)	(0.059)	(0.061)	(0.056)	(0.035)	(0.065)	(0.054)
exrec	0.341	-4.706	1.478	-5.224	-1.085	-5.557	-1.296	-1.212
	(0.916)	(2.527)	(1.914)	(7.343)	(2.543)	(3.550)	(4.006)	(4.591)
polcomp	0.735	4.492	0.048	2.116	0.428	6.444*	1.157	1.184
	(1.476)	(2.344)	(1.111)	(3.634)	(2.046)	(3.075)	(2.364)	(3.404)
N	923	924	1070	607	925	923	1033	607
CD Test P-value	0.000	0.261	0.389	0.0139	0.000	0.560	0.536	0.017
CD Test Statistic	4.100	1.121	0.860	2.459	3.458	0.581	0.618	2.391

Standard errors in parentheses

The CD Test P-value and Test Statistic represent the Pesaran Cd test and are calculated to test the null hypothesis of no cross-sectional dependence in the panel data.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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A List of countries and period of observations in study

Country Name	Period
Albania	1981-2018
Algeria	1970-2018
Angola	1981-2018
Antigua and Barbuda	1978-2018
Argentina	1970-2018
Armenia	1991-2018
Aruba	1987-2018
Australia	1970-2018
Austria	1970-2018
Azerbaijan	1991-2018
Bahamas, The	1970-2018
Bahrain	1981-2018
Bangladesh	1970-2018
Barbados	1970-2018
Belarus	1991-2018
Belgium	1970-2018
Belize	1970-2018
Benin	1970-2018
Bhutan	1981-2018
Bolivia	1970-2018
Bosnia and Herzegovina	1995-2018
Botswana	1970-2018
Brazil	1970-2018
Brunei	1975-2018
Bulgaria	1981-2018
Burkina Faso	1970-2018
Burundi	1970-2018
Cambodia	1994-2018
Cameroon	1970-2018
Canada	1970-2018
Cape Verde	1981-2018
Central African Republic	1970-2018
Chad	1970-2018
Chile	1970-2018
China	1970-2018
Colombia	1970-2018
Comoros	1981-2018
Congo	1970-2018
Congo, Dem. Rep.	1970-2018
Costa Rica	1970-2018
Cote d'Ivoire	1970-2018
Croatia	1991-2018
Cuba	1971-2018
Cyprus	1976-2018
Czech Republic	1991-2018
Denmark	1970-2018
Djibouti	1991-2018
Dominica	1978-2018
Dominican Republic	1970-2018
Ecuador	1970-2018
Egypt	1970-2018
El Salvador	1970-2018
Equatorial Guinea	1981-2018
Estonia	1981-2018
Ethiopia	1982-2018
Fiji	1970-2018
Finland	1970-2018
France	1970-2018
Gabon	1970-2018
Gambia, The	1970-2018
Georgia	1970-2018

Country Name	Period
Germany	1971-2018
Ghana	1970-2018
Greece	1970-2018
Grenada	1978-2018
Guatemala	1970-2018
Guinea	1987-2018
Guinea-Bissau	1971-2018
Guyana	1970-2018
Haiti	1970-2018
Honduras	1970-2018
Hong Kong SAR, China	1970-2018
Hungary	1970-2018
Iceland	1970-2018
India	1970-2018
Indonesia	1970-2018
Iran	1970-2018
Iraq	1970-2018
Ireland	1970-2018
Israel	1970-2018
Italy	1970-2018
Jamaica	1970-2018
Japan	1970-2018
Jordan	1976-2018
Kazakhstan	1991-2018
Kenya	1970-2018
Kiribati	1971-2018
Korea	1970-2018
Kuwait	1970-2020
Kyrgyz Republic	1988-2018
Lao PDR	1985-2018
Latvia	1970-2018
Lebanon	1989-2018
Luxembourg	1970-2018
Macao SAR, China	1983-2018
Madagascar	1970-2018
Malawi	1970-2018
Malaysia	1970-2018
Maldives	1996-2018
Mali	1970-2018
Malta	1970-2018
Marshall Islands	1982-2018
Mauritania	1970-2018
Mauritius	1977-2018
Mexico	1970-2018
Micronesia	1987-2018
Moldova	1990-2018
Mongolia	1982-2018
Montenegro	2001-2018
Morocco	1970-2018
Mozambique	1981-2018
Myanmar	1970-2018
Namibia	1981-2018
Nepal	1970-2018
Netherlands	1970-2018
New Zealand	1970-2018
Nicaragua	1970-2018
Niger	1970-2018
Nigeria	1970-2018

Country Name	Period
North Macedonia	1991-2018
Norway	1970-2018
Oman	1970-2018
Pakistan	1970-2018
Palau	1992-2018
Panama	1970-2018
Papua New Guinea	1970-2018
Paraguay	1970-2018
Peru	1970-2018
Philippines	1970-2018
Poland	1991-2018
Portugal	1970-2018
Qatar	2001-2018
Romania	1982-2018
Russia	1990-2018
Rwanda	1970-2018
Samoa	1983-2018
Saudi Arabia	1970-2018
Senegal	1970-2018
Serbia	1996-2018
Seychelles	1970-2018
Sierra Leone	1970-2018
Singapore	1970-2018
Slovak Republic	1985-2018
Slovenia	1991-2018
Solomon Islands	1981-2018
South Africa	1970-2018
Spain	1970-2018
Sri Lanka	1970-2018
St. Kitts and Nevis	1978-2018
St. Lucia	1978-2018
St. Vincent and the Grenadines	1970-2018
Sudan	1970-2018
Suriname	1970-2018
Swaziland	1971-2018
Sweden	1970-2018
Switzerland	1970-2018
Syrian Arab Republic	1970-2020
Tajikistan	1986-2018
Tanzania	1989-2018
Thailand	1970-2018
Timor-Leste	2000-2018
Togo	1970-2018
Tonga	1982-2018
Trinidad and Tobago	1970-2018
Tunisia	1970-2018
Turkey	1970-2018
Turkmenistan	1988-2019
Uganda	1983-2018
Ukraine	1988-2018
United Arab Emirates	1974-2018
United Kingdom	1970-2018
United States	1970-2018
Uruguay	1970-2018
Uzbekistan	1988-2018
Vanuatu	1980-2018
Venezuela	1970-2014
Vietnam	1986-2018
Yemen	1991-2018
Zambia	1970-2018
Zimbabwe	1970-2018

B Countries by income group

Table 18: list of countries groups by income

Income Group	Country name
High income	Antigua and Barbuda, Australia, Austria, Bahamas, The, Barbados, Belgium, Canada, Chile, Cyprus, Denmark, Finland, France, Germany, Greece, Guyana, Hong Kong SAR, China, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Kuwait, Luxembourg, Malta, Netherlands, New Zealand, Norway, Oman, Panama, Portugal, Saudi Arabia, Seychelles, Singapore, Spain, Sweden, Switzerland, Trinidad and Tobago, United Arab Emirates, United Kingdom, United States, Uruguay
Upper middle income	Argentina, Botswana, Brazil, China, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Fiji, Gabon, Guatemala, Indonesia, Iraq, Jamaica, Malaysia, Mauritius, Mexico, Paraguay, Peru, South Africa, Suriname, Thailand, Turkey.
Lower middle income	Algeria, Bangladesh, Benin, Bolivia, Cameroon, Congo, Cote d'Ivoire, Egypt, Ghana, Honduras, India, Iran, Jordan, Kenya, Kiribati, Lesotho, Mauritania, Morocco, Myanmar, Nepal, Nicaragua, Nigeria, Pakistan, Philippines, Senegal, Sri Lanka, Swaziland, Tunisia, Zambia, Zimbabwe.
Low income	Burkina Faso, Burundi, Central African Republic, Chad, Congo, Dem. Rep., Gambia, The, Guinea-Bissau, Madagascar, Malawi, Mali, Niger, Rwanda, Sierra Leone, Sudan, Syrian Arab Republic, Togo.

C Investigating the relation between trade openness proxies

The KOF Trade Globalization Index measures the economic dimension of globalization. This index reflects not only the actual economic flows like foreign direct investment but also the restrictions on these flows, such as tariffs and trade barriers. In essence, it provides a comprehensive picture of a country's involvement in the global economy.
The relationship between the KOF Trade Globalization Index and trade is quite direct: the index incorporates aspects of trade (among other factors) to gauge how globally integrated a country is in terms of economic transactions. Using the KOF Index alongside actual trade data can be valuable for a few reasons:

- **Broader Measurement**: While trade data typically measures the volume or value of imports and exports, the KOF Index captures a wider range of interactions and restrictions. This includes trade barriers, tariffs, and the diversity of trading partners, offering a more holistic view of a country's global economic integration.
- **Complementary Information**: The KOF Index can complement trade data by providing context. For example, high trade volumes in a country with high trade barriers (as captured by the KOF Index) might indicate different economic dynamics than similar trade volumes in a country with low trade barriers.
- **Analytical Depth**: When analyzing economic phenomena, using both the KOF Index and trade data can provide a more nuanced understanding. For instance, in economic models or empirical analyses, the KOF Index might capture the effects of globalization policies or openness that are not directly observable through trade figures alone.

We investigate the relationship further by regressing trade on the KOF index.

Table 19: Relation between two trade proxies

Trade as dependent variable	
	(1)
KOFTrGIdf	1.961***
	(0.019)
constant	-19.200***
	(1.054)
N	7958
adj. R^2	0.566

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The positive coefficient for KOFTrGIdf, 1.961 with a very high statistical significance, suggests a strong positive relationship between the KOF Trade Globalization Index and the dependent variable in the model. The adjusted R-squared has a value of 0.566 suggests that around 56.6% of the variability in your dependent variable is explained by the model. In summary, including both the KOF Trade Globalization Index and trade data in an analysis allows for a richer and more nuanced understanding of a country's economic integration and its impact on various economic outcomes.