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-RESEARCH ARTICLE-

INFLATION CONNECTEDNESS NETWORK IN INDONESIA

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—Abstract—

Our investigation delves into the interregional inflation interconnectedness and its ramifications within the Indonesian economy, adopting a Connectedness network framework. Methodologically, we employ a time series analysis utilizing the Generalized Vector Autoregressive (VAR) model, specifically the Koop, Pesaran, Potter, and Pesaran, Shin (KPPS) H-step ahead error variance decomposition model. The crux of our inquiry lies in the quantification of the total inflation spill over index in Indonesia, which we ascertain to be 78.24%. This empirical finding underscores a

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substantial spillover effect across the six provinces over the entire observational period. Notably, our analysis highlights Java, Sulawesi, Kalimantan, and Balinusra as pivotal regions acting as transmitters within the Connectedness Network Inflation in Indonesia. These findings carry implications for policymaking, advocating for governmental attention towards the determinants of stability in interregional inflation rates, particularly emphasizing the role of physical infrastructure connectivity.

Keywords: Inflation, Generalized VAR, Forecast Error Variance Decomposition (FEVD), Directional spill over, Connectedness Network

JEL Classification: C4, E31, R12

INTRODUCTION

The dynamics of inflation in Indonesia exhibit fluctuations influenced by spatial externality factors. Interconnectedness among regions in Indonesia, alongside similarities in inflation patterns among neighbouring provinces, can engender a spillover effect from one province to another. This study innovatively models Indonesian inflation dynamics through the lens of an inflation connectedness network and leverages time series data structures. However, the scope of this research remains constrained, particularly within the context of Indonesia.

Traditionally, investigations into the determinants of inflation predominantly concentrate on headline inflation, often side-lining core inflation. This aspect is integral to Bank Indonesia's monetary policy deliberations. Nonetheless, an exhaustive understanding of headline inflation formation in Indonesia necessitates consideration of non-core inflation, characterized by substantial fluctuations, notably stemming from supply-side inflationary shocks originating from volatile food prices and administered inflation.

Insights gleaned from scrutinizing non-core inflation due to supply or distribution disruptions, as well as administered price policies—particularly regarding fuel oil and energy in Indonesia—can furnish recommendations pertinent to ensuring smooth foodstuff distribution and addressing fundamental needs across regions. Consequently, the government can calibrate the quantity and quality of infrastructure, such as roads, bridges, ports, and airports, by discerning the level of inflation connectedness between regions in Indonesia. The inflation connectedness network delineates key transmitter and receiver regions shaping inflationary trends in Indonesia.

Inflation serves as a principal gauge for appraising macroeconomic stability, exerting influence on price fluctuations across various commodities within district and city areas. In Indonesia, inflation emanates from diverse sources, including shocks amenable

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to Bank Indonesia's intervention. However, fluctuations in inflation can also stem from supply-side shocks, encompassing production and distribution disruptions, alongside governmental policies. These non-monetary factors precipitating inflation underscore the multifaceted nature of inflationary dynamics.

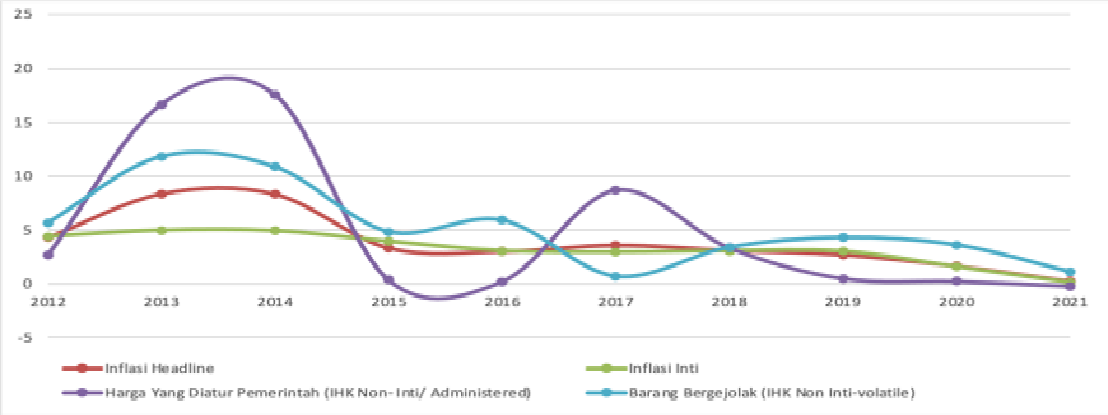

Figure 1: Characteristics of Inflation in Indonesia (2012-2021)

Figure 1 elucidates the dynamics of non-core inflation (supply side), characterized by its pronounced volatility and substantial fluctuations. This attribute is evident in the non-core inflation data spanning 2012-2013, 2014-2015, 2016-2017, and 2020-2021 periods. Ultimately, these supply-side inflationary shocks play a pivotal role in shaping the national pattern of headline inflation. Given the interconnected regional characteristics and resources across Indonesian provinces, this headline inflation pattern harbours the potential for spillover effects between regions.

In Indonesia, disparities in inflation rates among provinces stem from the influence of price differentials between adjacent provinces. Widya et al. (2021) discerned that the price index established by the government in a neighbouring province significantly influences inflation. Employing a dynamic model, namely the spatial multivariate regression model with spatial dependence manifesting in response and predictor variables, known as the Spatial Durbin Model (SDM), this finding corroborates the theory that while an increase in the government-set price index yields a marginal impact, its situational and indirect effects are noteworthy. For instance, a rise in fuel prices precipitates escalations in prices of fuel- and food-related goods and services, which vary across provinces, exacerbating inflationary pressures.

The inflation rate assumes a pivotal role in determining price fluctuations for each commodity at the Regency/City or national level. Monthly inflationary changes ensue from a confluence of price fluctuations across diverse goods and services. The propensity for inflation distribution patterns in Indonesia is marked by concentration in

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specific areas owing to spillover effects from neighbouring regions, underpinned by geographical proximity, shared characteristics, and interconnected factors among provincial regions. Economic interlinkages between regions wield influence over the aggregate headline inflation value through the impact of non-core Consumer Price Index (CPI) values on the supply side.

Indonesia, ranked 16th globally in nominal GDP, is poised to ascend to the fifth position by 2030, with an estimated GDP of USD 5.42 trillion. As one of the fastest-growing economies, Indonesia has grappled with significant macroeconomic volatility, uncertainty, complexity, and ambiguity. This backdrop engenders notable fluctuations in inflation levels over time. Moreover, these fluctuations permeate the connectivity landscape between provinces across six provincial groupings—Sumatra, Java, Kalimantan, Sulawesi, Balinusra, and Mamapapa—categorized based on geographical proximities between regions.

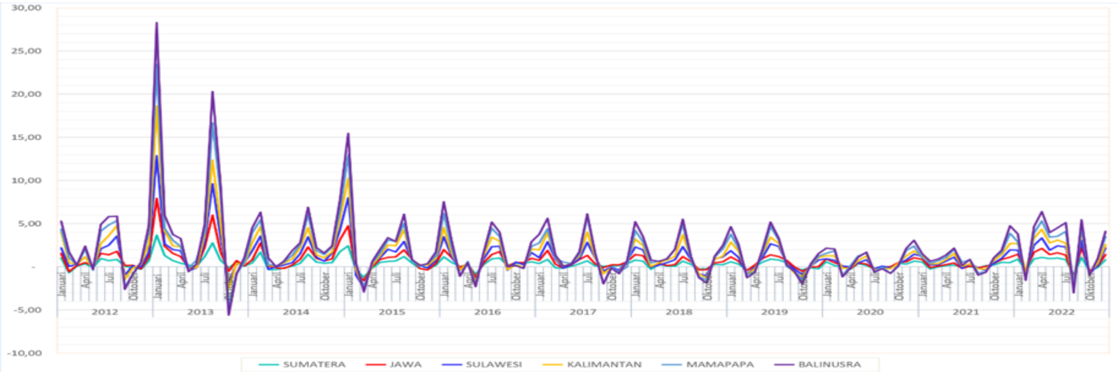

Figure 2: Monthly Inflation Patterns between Regions in Indonesia for the Period December 2002 - December 2022

Figure 2 elucidates the inflation dynamics, showcasing a consistent movement pattern across all provincial groups in Indonesia. These regional clusters encompass Sumatra, Java, Sulawesi, Kalimantan, Bali-Nusa Tenggara (Balinusra), and Maluku-Papua (Mamapapa). Notably, every quarterly inflation rate alteration initially exhibits elevated levels, particularly in November, December, and January. Subsequently, a discernible trend emerges, indicating a decrease in the inflation rate, following a nearly uniform pattern. In Indonesia, inflation tends to decline from February to April, only to surge again in the second quarter, spanning May to July, before subsiding once more in the final quarter, from August to October. The cyclicality of regional inflation in Indonesia tends to peak again in December and January, mirroring the preceding quarterly inflation pattern.

Characteristics of the inflation rate, gauged by distribution patterns and the oscillatory inflation movements among provincial groups in Indonesia, suggest the potential for

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spillover effects within the nation. Consequently, the identification of spill over econometric models proves apt for modelling, elucidating the interplay among provincial regions in Indonesia in shaping inflationary levels. Ultimately, the variability in inflation rates across Indonesian provinces constitutes a pivotal factor in shaping the national inflation rate.

Indonesia's inflation predicament, characterized by double-digit increases, is attributable to inadequacies in the government's administered price policies, resulting in diminished purchasing power among the populace. Theoretical perspectives on the drivers of inflation in Indonesia appear to be influenced by macroeconomic variables, eliciting direct responses from the government through interest rate adjustments. Nonetheless, inflation volatility persists, signifying that the multifaceted nature of the inflationary challenge may elude singular interventions by the government. Despite this, efforts to mitigate inflation challenges in Indonesia have been deemed effective, maintaining inflation at a low and stable level.

Innovative programs aimed at preserving supply stability and ensuring smooth distribution are anticipated to uphold the Consumer Price Index inflation. The significance of connectivity studies in facilitating the seamless distribution of essential supplies warrants broader and more comprehensive validation. This emphasis on connectivity studies underscores a pivotal facet of a nation's developmental trajectory, suggesting that contemporary economic development policies incorporate dimensions that scrutinize indirect influences, such as spillover effects.

LITERATURE REVIEW

Since the onset of the financial crisis in the Atlantic and the ensuing pandemic, inflation has emerged as a complex indicator, confounding economic policymakers, particularly in developed nations striving to maintain inflation at subdued levels. Supply-side inflationary shocks, coupled with escalating commodity prices, have exerted upward pressure on prices, instigating debates among researchers seeking the most apt models for understanding inflation dynamics.

The discourse on spillover effects has garnered significant attention within academic circles, primarily explored through panel data and time series analyses. While spillover effects have been extensively scrutinized in panel data studies encompassing regional economic variables, human resource economics, and development economics, their examination within time series data structures, particularly concerning inflation variables, remains relatively sparse. This gap in research is notable as inflation constitutes a crucial macroeconomic and monetary variable influencing a country's overall economic stability.

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This study assumes significance in delving deeper into the intricacies of inflation movements and fluctuations across various provinces in Indonesia. The ripple effects of inflation within one region not only dictate the stability and trajectory of inflation in other regions but also underpin the overarching national inflation target.

Demonstrating the existence of spillover effects and identifying factors determining inflation within a region, where the region serves as a transmitter, can furnish actionable insights for governmental interventions aimed at mitigating supply-side inflation shocks. Ensuring robust infrastructure and facilitating the seamless distribution of essential goods and services are imperative components of such interventions. Moreover, studying the determinants of inflation stemming from the supply side, notably volatile food prices and administered inflation factors, underscores the necessity for a holistic policy approach encompassing both monetary and real sector policies.

Development policies should be tailored to confer tangible benefits to diverse regions, with spatially informed analyses of macro variables constituting an integral part of the developmental process. Addressing spatial disparities between regions necessitates proactive government intervention, with more efficient policy planning aimed at attenuating regional variations in macroeconomic indicators, particularly inflation.
The relationship between inflation variance and output levels manifests differently across countries characterized by varying degrees of price volatility. Countries experiencing pronounced price fluctuations tend to exhibit wider disparities between output levels and price levels relative to the average inflation and output levels, as posited by (Lucas, 1973). Conversely, countries with more stable price levels demonstrate contrasting dynamics, underscoring the intricate interplay between inflation dynamics and economic output levels.

The fluctuating nature of inflation manifests through pronounced volatility, characterized by sharp price increases during peak periods followed by declines during off-peak periods. This volatility is discernible in residual variance values, which deviate from the assumption of homoscedasticity. Consequently, an overview of spillover effects can be garnered through the application of the VAR model.

Sims (1980) introduced the VAR model, offering an estimation solution for the presence of endogenous variables on both sides of the equation, encompassing both dependent and independent variables. VAR posits interdependence among all economic variables, facilitating the projection of time series data and the analysis of dynamic impacts among variables within a system of equations. The model elucidates that each variable within the system depends on its own past movements and those of other variables within the equation system. VAR simultaneously analyses multiple endogenous variables within a single model.

The conceptual framework of the VAR model underwent refinement by Koop et al. (1996), and Pesaran and Shin (1998), resulting in the generalized VAR model, commonly known as the KPPS model. The conventional VAR model's sensitivity to variable order necessitated the development of the generalized VAR concept by KPPS. Unlike the traditional VAR, the KPPS model does not hinge on variable order, thereby ensuring consistent output regardless of variable sequence. Consequently, when employing a spill over time series data structure, the preferred model choice is the generalized VAR, along with the utilization of generalized FEVD values.

Diebold and Yilmaz (2009, 2012) examined the interdependence relationship between asset returns or volatility, segregating the research period into crisis and non-crisis epochs across 19 global equity markets since the early 1990s. Their findings delineate distinct characteristics in spill overs from return values and spill over volatility dynamics. While spill over patterns in return values exhibit a gradual upward trend devoid of discernible patterns, spill over volatility showcases intermittent bursts without a consistent trend. Leveraging the Vector Autoregressive framework alongside the Forecast Error Variance Decomposition method, the study elucidates daily volatility spill overs across stock markets, bonds, foreign exchange, and commodity markets in the US from January 1999 to January 2010. Notably, significant volatility fluctuations were observed across the four markets during the research period, particularly amidst the global financial crisis commencing in 2007, with volatility spill overs from the stock market to other markets intensifying, notably during the collapse of Lehman Brothers in September 2008.

Civelli and Zaniboni (2014) investigated the enduring nature of supply-side inflation, employing GDP deflator variables, commodity price index, interest rates, and bank reserves. They observed a persistent pattern of inflation response to monetary shocks in the supply side of monetary policy transmission. Disruptions on the supply side stemmed from government policy variables and various forms of disruptions such as natural disasters and distribution issues. The researchers utilized the VAR (Vector Auto Regression) method, known for its efficacy in predicting time series data due to the presence of disturbance factors.

Examining supply-side inflation in Indonesia from 1984 to 2013, Rahman (2015) analysed several macroeconomic variables including the Wholesale Price Index (IHPB), Consumer Price Index (CPI), Rupiah exchange rate, and real wages. They found that fluctuations in inflation rates were significantly influenced by supply-side factors. The volatility of supply-side inflation characteristics was assessed using the ECM (Error Correction Model) method to examine its impact on inflation, considering both short-term and long-term lag effects of independent variables.

Discussing the concept of spill overs, particularly the transmission of international inflation through input linkages, Auer et al. (2017) examined inflation, exchange rates, industry-level, and producer price variables across countries. They highlighted the substantial contribution of global production input-output linkages to domestic inflation, utilizing Input-Output analysis to assess the effects of production cost shocks and governmental policies on economic sector progress.

Kang et al. (2019) employed the Global Vector Autoregression (GVAR) wavelet coherence model and spill over index to investigate the interrelationships between countries. The spill over index, determined through the Pairwise Comparison Matrix, evaluates the performance effects of paired variant values, measuring the degree of integration between the researched countries.

Stann and Grigoriadis (2020) identified a spillover effect of monetary policy announcements by the European Central Bank (ECB) on Russia and Eastern European countries. Utilizing OLS tests, they estimated models with monetary policy dummy variables and seven financial variables across eleven Eastern European countries and Russia. Bilateral integration with the Eurozone emerged as the primary determinant of the spill over impact, influencing appreciation of Eastern European currencies, stock market indices, and long-term government bond yields.

Haque et al. (2021) applied the time-varying parameter VAR (TVP-VAR) technique to examine volatility and uncertainty shocks in inflation within the United States. Their research revealed a negative response to inflation post-21st century, attributing stochastic volatility values to inflation dynamics. The study highlighted the supply-side origins of uncertainty shocks, leading companies to respond with price increases, while recessions triggered temporary deflationary pressures.

Congregado and Esteve (2022) analysed the classical inflation model in Spain spanning from 1830 to 1998. They found cointegration between money growth and inflation, disregarding speculative bubbles of rational expectations. Through unit root tests and the Philips-Peron stability test, they assessed the behaviour and period of inflation rates, ultimately confirming linear cointegration in the regression model with modifications to the modelling structure.

Aras et al. (2022) emphasized the significance of identifying the most suitable methodology for forecasting inflation, given the ample availability of data. The challenge arises from the high correlation among predictor values in forecasting inflation. To address this issue, several researchers have turned to Machine Learning (ML) methods. These techniques transform the functional form of the inflation forecasting model into a factor model, converting the forecast equation into a nonlinear form. Through a series of comprehensive experiments, particularly focusing on the case study of Turkey, predictions of inflation values are derived. Developing countries contend with volatility, uncertainty, fluctuations, and high inflation rates, making the ML tree-based ensemble model a particularly accurate technique for predicting inflation. However, despite ML's effectiveness in handling time series data structures, its capacity to predict macroeconomic variables remains limited due to challenges in balancing trade-offs and variance bias.

Azad and Serletis (2022) investigated the spillover effect of uncertainty in the monetary policy of the United States on seven developing countries, including Indonesia, Chile, Brazil, Colombia, Mexico, Poland, and South Africa. Employing a multivariate GARCH-in-Mean (VAR) vector autoregression analysis based on the Taylor rule type in each country, the research method also involved a multivariate structural VAR model to identify short and long-term effects. The empirical evidence gathered, alongside robustness checks, confirmed the negative impact of uncertainty in US monetary policy on the macroeconomic and financial fundamentals of the developing countries.

Park et al. (2023) examined the inherently ambiguous nature of the inflation model, which influences consumption behaviour, investment decisions, retirement planning, and life insurance choices. Market price volatility and correlation parameters are perceived as the aggregated value of bond indices in the stock market. Their modelling approach combines classical dual approach techniques with G-stopping time theory, utilizing a derivative of the integral equation to mitigate ambiguity in volatility and correlation, thereby aiming to construct a robust equation.

Huang et al. (2023) assert that inflation introduces risks to portfolio investments, as evidenced by mean-variance modelling. This modelling approach reveals the amplification of investment risk amidst linear uncertainty in inflation, prompting investors to decrease allocations to risky assets. The impact of inflation is contingent upon the proportion of investment in risky assets; higher allocations correspond to diminished inflation levels. Despite being foundational to modern portfolio theory, mean-variance modelling operates under the assumption that investors exclusively face risk on securities, disregarding other sources of risk such as background risk, complicating the management of inflation variance.

Araujo and Gaglianone (2023) employed the ML method to forecast Brazil's inflation rate using 501 datasets comprising 167 macro and financial variables. ML methodology, rooted in data-driven pattern recognition, integrates various traditional econometric techniques like VAR, ARMA, factor models, and Phillips curves. The nonlinear dynamics of inflation data pose challenges to forecasting, with ML models offering insights into macroeconomic conditions based on inflation variables. The uncertainty surrounding inflation rates presents a significant challenge for policymakers and economic agents in formulating investment decisions.

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Bobeica and Hartwig (2023) utilized the Gaussian-Vector Autoregressive (VAR) parameter technique to analyse the impact of inflation on Euro area countries during the COVID-19 period. Employing fat-tailed residuals in combination with multi-equation modelling, rather than a Gaussian distribution, was imperative to maintain modelling robustness. To enhance accuracy, researchers augmented the model with external information using the Survey of Professional Forecasters (SPF) technique. The COVID-19 pandemic induced substantial variations in observations of real macroeconomic activity and labour market indicators, distorting coefficient estimates since the analysis scope in 2020. Standard Gaussian BVAR models of inflation similarly yield distorted economic inferences under these conditions.

Zhang et al. (2020) conducted an investigation into the spatial transmission of stock market spillover effects among G20 nations, focusing on the spill over volatility network over the period spanning January 2006 to December 2018. Their study elucidated how volatility spill overs and spatial dynamics within the G20 stock market disseminate financial risk. Employing the GARCH-BEKK model, they identified the volatility network within the G20 stock market. Moreover, the spatial Durbin model was employed to capture both direct and indirect spatial effects. Their analysis revealed a positive correlation between the volatility of inflation, stock markets, government debt, and systemic risk. Notably, the indirect spillover effect on systemic risk exhibited a greater magnitude than the direct spillover effect, highlighting the significance of connectedness analysis in understanding social linkages over time.

Tumala et al. (2021) investigated the propagation of financial and trade monetary policy shocks across the US, Europe, China, and SSA countries, specifically Nigeria and South Africa. Employing the GVAR model, they analysed the impulse response function to inflation shocks in the SSA economy originating from the US, Europe, and China. Tight monetary policies in the US and EU were found to influence South Africa's inflation rate significantly. Furthermore, shocks emanating from the US, Europe, and China exerted considerable effects on the monetary policies of developing countries.

Yao and Li (2023) employed the Garch-Midas-GAS method to compute conditional value at risk (CoVaR) and elucidate the risk spillover effect on the stock market. Their modelling approach incorporated stock market utility patterns and integrated them with the Generalized Autoregressive Score mechanism to establish dynamic parameters. Their research demonstrated that CoVaR calculation outperforms other models by providing a comprehensive depiction of the risk spill over relationship. Notably, transmissions from the stock markets of China and the United States conveyed high-risk information influencing investment decisions in other countries. Data from the Shanghai Composite Index and the S&P 500 Index spanning 2504 observation periods from April 1, 2013, to February 28, 2022, were utilized in their analysis.

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Yu et al. (2023) employed a Non-Parametric Time-Varying Autoregressive Distributed Lag (TV-ARDL) model to examine inflation persistence as an alternative to Phillips curve analysis, allowing parameters to fluctuate over time. Their study revealed that inflation remains a non-stationary time series variable, with time-varying volatility. They found that American inflation declined before the 2007-2009 global financial crisis, rebounding thereafter until 2022. Inflation persistence indicates the duration required to mitigate inflationary shocks, reflecting the economy's susceptibility to external influences, which may vary based on economic conditions and monetary policies.

METHODS

This study employs quantitative research methodologies, characterized by systematic empirical analysis. Monthly data series spanning from 2011 to 2022 are utilized for variables across all provinces in Indonesia. These data sets are sourced from secondary publications by the Central Statistics Agency (BPS) and relevant government bodies, along with prior research aligned with the study's focus.

The dataset covering the 2011-2022 period is employed to scrutinize inflation grouping patterns and the spillover effects of inflation variables across all districts and cities in Indonesia. The research encompasses the entirety of Indonesia's provinces, segmented into distinct regions: Sumatra, Java, Kalimantan, Sulawesi, Bali-NusaTenggara/Balinusra, and Maluku-Papua/Mamapapa.

The Sumatra region comprises Aceh, North Sumatra, West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, Bangka Belitung, Riau Islands, and Lampung. The Java region encompasses DKI Jakarta, West Java, Central Java, East Java, DI Yogyakarta, and Banten. The Kalimantan region includes West Kalimantan, East Kalimantan, Central Kalimantan, South Kalimantan, and North Kalimantan. The Sulawesi region comprises North Sulawesi, West Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, and Gorontalo. The Balinusra region consists of Bali, East Nusa Tenggara, and West Nusa Tenggara. Lastly, the Mamapapa region includes Papua, Maluku, and North Maluku provinces.

Analysis Steps

Data Stationarity Test

The data stationarity assessment in this research employed the Phillips Perron method. The Phillips Perron test (PP test) scrutinizes the statistical t-value of the regression coefficient pertaining to the observed variable (X). A determination of data stationarity

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is made when the Phillips Perron (PP) value surpasses the critical threshold at a significance level (α) of 5% or 10%. In such cases, the data is classified as stationary. Transformation of non-stationary data into stationary form can be achieved through straightforward differencing techniques. Typically, the first-order differentials indicate stationary data. Subsequently, a unit root test is imperative. Should the original data demonstrate stationarity, it can be deemed ready for subsequent analyses. The VAR model necessitates data integration to the same order. In the event of non-stationarity at a certain level, the overall dataset is processed as first-order difference data.

Determining of Optimum Lag

The employment of dynamic models in analysing time series data entails that the impacts of unit changes in explanatory variables manifest over a specified duration. This implies that alterations in a particular explanatory variable may only be discernible after a certain time lag. Lag, characterized by a temporal discrepancy, can arise from institutional factors such as policy implementation or the inertia of economic agents who do not promptly adjust their behaviours following changes in external conditions, possibly influenced by psychological factors. Identifying the optimal lag in Vector Autoregression (VAR) analysis can be accomplished using various information criteria, including the Likelihood Ratio (LR), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Final Prediction Error (FPE), and Hannan-Quinn Information Criterion (HQIC).

Vector Autoregression (VAR) Model Estimation

The VAR model estimation entails determining an optimal lag based on calculation criteria. VAR analysis prioritizes technical forecasting, Impulse Response Function (IRF), and Forecast Error Variance Decomposition (FEVD). The IRF function elucidates the future k-period expectations of prediction errors for a variable resulting from innovations in other variables. It reveals the duration of the shock effect of a variable on other variables until the effect dissipates or returns to equilibrium. IRF serves as a tool for tracing the impact of a shock on a variable across the system for a specified duration.

FEVD is a crucial component of the VAR model, providing insights into the dynamic system's description. It disentangles variance from innovation under the assumption of uncorrelated innovation variables. FEVD furnishes information about the proportion of movement in the influence of a shock on one variable on the shock of another variable in both current and future periods. The FEVD results delineate the strength of the Granger causality relationship that may exist between variables. A variable exhibiting a substantial forecast error variance relative to others indicates the presence of a robust Granger causality relationship.

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FEVD serves as a decomposition method for discerning alterations in a variable's value resulting from shocks originating from the variable itself or from other variables. The residual variance s (s = 1,2,..) at the subsequent step is dissected, delineating the portion stemming from the variable itself and that arising from other variables.

Analysis of Spill over Data Time Series

Aleksandra and Szafranek (2015) conducted an examination into the ramifications of inflation spill overs among EU nations, employing the Deibold and Yilmaz spill over index methodology. Their analysis unveiled a discernible spill over impact, indicating a decline in inflation rates across several countries since 2010, with the nadir reached in 2014. Subsequently, a reversal occurred in the subsequent year, with spillover effects manifesting in the domain of non-energy industrial goods and services, thereby designating the Euro Area as a conduit for inflation transmission. The repercussions of Euro Area inflation spill over further precipitated an upswing in headline inflation rates while concurrently diminishing core inflation levels across most nations.

Verification of spillover effects through the time series spill over approach involves assessing the rho coefficient or spatial lag of significant variables. Spill over, inherent in time series data, signifies the propagation of effects from an event to other entities, typically denoted as shocks. These shocks, prevalent in the macroeconomic landscape, encompass phenomena such as the Covid-19 pandemic and trade conflicts.

Addressing the repercussions of shock-induced spill over necessitates a multifaceted policy approach targeting all pertinent elements and variables. To substantiate the spillover effect on Indonesia's inflation dynamics, comprehensive inflation analysis units across diverse provinces in the country are imperative. Employing monthly inflation data from each province, the research utilizes a time series data framework to scrutinize inflation spillover effects within Indonesia's provincial domains, thereby elucidating spill over phenomena both within and across regions.

In this study, the VAR model serves as a tool to capture the interplay among variables. Within the Spill over framework, the VAR model's utility transcends mere impact assessment, rendering the conventional OLS techniques insufficient for estimating outcomes. The time series spill over analysis undertaken in this research scrutinizes the propagation of shocks from one variable to others, employing the FEVD approach. FEVD accommodates the intricacies of data structures, catering to the order and characteristics of variables. Subsequent developments in the research scope delve into both total spill over and directional spill over, drawing from the works of Koop et al. (1996) and Pesaran and Shin (1998), who extended the VAR framework into the generalized VAR, commonly referred to as the KPPS model.

The FEVD technique, integral to the KPPS framework, encompasses an analysis stage known as the KPPS H-step ahead error variance decomposition. This equation predicts future error values, facilitating the computation of variance. The outcomes of this stage elucidate multiple equation points, as FEVD posits predictive capabilities for everyone analysed. The KPPS H-Step ahead error variance decomposition is represented by the following formula:

KPSS H-step ahead error variance decomposition = $\theta_{ij}^{g}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma\, e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma\, A_h' e_i)}$ (1)

Variance share is the fraction of the H- Step ahead error variances in forecasting xi that are due to shocks to xi. Notation i = 1,2,……N cross variance shares (spill overs) that is as the fractions of the H-Step ahead error variances in forecasting xi that are due to shocks to xj for i, j = 1,2,…..N, that *i ≠j.* Formula 8 above denoted the KPPS H-Step ahead forecast error variance decompositions by $\theta_{ij}^{g}(H)$, for H = 1,2,………where Σ is the variance matrix for the error vector ε, σjj is the standard deviation of error term for the jth equation as e_i is the selection vector with one as the ith element and zero otherwise.
Rows of variance decomposition table is not equal to 1, which is 1: $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$.

In the computation of the spill over index, each element in the variance decomposition matrix is normalized by the sum of elements in its respective row, as indicated by formula 9. This normalization ensures that each entry in the variance decomposition matrix is scaled appropriately. Additionally, to achieve a total sum of 1 for all values, the KPSS H-step ahead error variance decomposition is further normalized, such that the cumulative sum equals 1. The normalized form of the KPSS H-step ahead error variance decomposition is expressed as follows:

Normalized sum equals to 1 = $\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}$ (2)

During this stage, it becomes apparent which elements hold the highest significance. Formulas (1) and (2) outlined above represent a generalized VAR incorporating the concept of generalized FEVD. This approach enables the comprehensive exploration of phenomena and allows for the quantification of both total volatility spill over and directional spill over variables. For each observed variable within a given time series period, there exists a numerical indication of its self-influence and its interrelations with other variables during that period. The analysis of a variable is assessed through the error value across time periods.

As per Diebold and Yilmaz (2012), total volatility spill overs are derived from the EFVD outcomes within a generalized VAR framework, indicating the impact of one

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variable's volatility on others. Data pertaining to each individual period is denoted as directional spill overs. Two perspectives on directional spill overs are considered: how spill overs from region I are influenced by all analysed regions.

In the context of this research's inflation case study, the estimation results will examine the manner in which inflation volatility spill over originating in region A is influenced by regions B, C, D, and others. Conversely, it will also assess how volatility spill over from region A propagates to all other areas under analysis. These dual perspectives on directional spill overs can be elucidated through the formula presented below:

Total volatility spill overs index = $S^g(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100$ (3)

Formula 2 serves as the KPPS equivalent of the Cholesky factor-based measure employed by Diebold & Yilmaz (2009). The total spill over index quantifies the extent of volatility shock spill overs across four asset classes on the overall forecast error variance.

Directional spill overs = $S_{i\cdot}^{g}(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100$ (4)

Directional spill overs = $S_{\cdot i}^{g}(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100$ (5)

The two concepts of directional spill overs can be discerned through a comparative analysis of influence, indicating the variance between the region exerting greater influence and the one predominantly affected by other regions, termed as Net spill over. Typically, a smaller region experiences greater influence from a larger one. The formulation for Net spill over is articulated as follows:

Net spill overs = $S_i^g(H) = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H)$ (6)

Broader expansion concerns the interconnection between a given region and another pair of regions, termed as net pairwise spill overs. The concept revolves around assessing the disparity between the impact magnitude of shocks transmitted from country A to B and vice versa. By examining the reciprocal relationship between two pairs of regions, net pairwise spill overs unveil the predominant influence. The formulation for net pairwise spillovers can be articulated as follows:

Net pairwise spill overs = $S_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}_{jk}^{g}(H)} \right) \cdot 100 =$

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$$\left(\frac{\tilde{\theta}_{ji}^{g}(H)-\tilde{\theta}_{ij}^{g}(H)}{N}\right)\cdot 100 \qquad (7)$$

The above equations are arranged based on covariance stationary N-variable VAR(p) $X_t = \sum_{i=1}^{p} \emptyset_i X_{t-i} + \varepsilon_t$, where $\varepsilon \sim (0, \Sigma)$, is a vector of distributed disturbances.The moving average is $X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$. Meanwhile N x N coefficient matrices A_i obey the recursion $A_i = \emptyset_i A_{i-1} + \emptyset_2 A_{i-2} + \cdots + \emptyset_p A_{i-p}$, with A_0 being an N x N identity matrix and with $A_i = 0$ for i < 0. The moving average coefficients, recognized as transformations such as impulse response functions or variance decompositions, play a crucial role in elucidating the dynamics of the system. They serve as essential elements for understanding system dynamics. Variance decompositions elucidate the forecast error variances of each variable, attributing them to various systemic shocks. Notation x_i that is due to schocks to x_i. $\forall_i \neq i$. for each i, obtained from the fraction of the H-Step ahead error variance in forecasting x_i.

RESULTS

In this study, the examination of inflation spill overs in Indonesia relies on the generalized VAR time series econometric model. The VAR model necessitates fulfilling the stationarity criteria for all variables and excluding any trends. Identification of a stochastic trend in the data implies the presence of both long-term (long run) and short-term (short run) components. Hence, addressing the stochastic trend in this data requires integrating the concept of cointegration and error correction, or modelling time series data that is cointegrated and non-stationary. This modelling framework is also referred to as the restricted VAR model.

Stationarity Test

Table 1. Stationarity Test of VAR Inflation in Indonesia

DATA	DICKEY-ULLER	TRUNCATION LAG PARAMETER	P-VALUE
SUMATRA	-8.4708	4	0.01
JAVA	-8.24	4	0.01
SULAWESI	-9.8927	4	0.01
KALIMANTAN	-8.2928	4	0.01
MAMAPAPA	-9.7465	4	0.01
BALINUSRA	-8.1178	4	0.01

Source: Processed data, 2023

Table 1 presents the VAR Inflation Stationarity test results for Indonesia. The data, represented in log volatility, indicates that all variables exhibit stationarity at the same level, specifically at the first difference. The Phillips-Perron Unit Root Test conducted for the regions of Sumatra, Java, Sulawesi, Kalimantan, Mamapapa, and Balinusra

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demonstrates a notable p-value at a 1% significance level for each region. The significant value obtained from the Phillips-Perron Unit Root Test suggests the suitability of conducting the inflation spill overs test in Indonesia using the VAR approach.

Determining of Optimum Lag

Determining the optimal lag for VAR modelling is a crucial step in this research. Various information criteria, including the Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), Final Prediction Error (FPE), and Hannan-Quinn Information Criterion, are employed for this purpose. The outcomes of the optimal lag test are provided in Table 2.

Table 2. Determining of Optimum Lag Inflation in Indonesia

AIC(n)	**HQ(n)**	**SC(n)**	**FPE(n)**
1	1	1	1
Criteria	1	2	3
AIC(n)	-12.58619	-12.57493	-12.41470
HQ(n)	-12.15382	-11.81828	-11.33377
SC(n)	-1.152207	-1.071273	-9.754406
FPE(n)	0.0003422182	0.0003475473	0.00004120356

Source: Processed data, 2023

Table 2 represents a crucial step in selecting the optimal lag for the VAR model. Model selection is conducted based on information criteria, aiming to minimize values for AIC, HQ, SC, and FPE. The information criterion tests reveal that lag 1 exhibits the smallest values across all criteria: -12.58619 for AIC, -12.15382 for HQ, -1.152207 for SC, and -0.00003422182 for FPE. Consequently, lag 1 is chosen for the VAR parameter estimation process. Thus, the estimated VAR equation takes the form of VAR (1). The output in Table 2 indicates the results of the optimal lag analysis, which leads to the estimation of coefficients for the VAR equation.

Effect of Volatility Spill over

Total Spill over Index

The process of demonstrating the inflation spillover effect across all provinces in Indonesia can be elucidated through the examination of the total spill over index. The results of the total spill over index test are summarized in Table 3.

Table 3 delineates the regions acting as sources and recipients of inflation spill overs. Specifically, Java, Sulawesi, Kalimantan, and Balinusra are identified as transmitter regions, while Sumatra and Mamapapa function as recipient regions. Each column

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provides insights into the magnitude of spill overs originating from different transmitter regions to Sumatra. For instance, the spill over from Java to Sumatra accounts for 18.71488%, while that from Sulawesi totals 14.96590%. Similarly, the overflow from Kalimantan to Sumatra is estimated at 15.41755%, whereas that from Balinusra stands at 16.30632%. These estimates, presented in the respective columns, represent the pairwise portions of spillover effects to other regions.

Table 3. Total Spill over Index Inflation in Indonesia

	To	From	Net	Transmitter
SUMATRA	75.84975	76.35867	-0.5089213	FALSE
JAVA	87.50788	79.0721	8.4357848	TRUE
SULAWESI	80.67842	78.94064	1.7377752	TRUE
KALIMANTAN	79.79019	79.18247	0.6077246	TRUE
MAMAPAPA	63.7462	76.71235	-12.9661542	FALSE
BALINUSRA	81.89109	79.1973	2.6937909	TRUE

Source: Processed data, 2023

Furthermore, Table 3 also illustrates the inflow into each region based on the values in each row. It delineates the spill over contributions received by Sumatra from various transmitter regions. For example, the spill over from Sumatra to Sumatra itself is calculated at 23.64133%, whereas the spill over from Java to Sumatra is 18.71488%. Similarly, the spill over from Sulawesi to Sumatra is measured at 14.96590%, while that from Kalimantan is 15.41755%. These estimations, depicted in the respective rows, represent the pairwise components of spillover effects originating from other regions.

The concept of directional spill overs elucidates the influence of spillover effects received by a specific provincial area, stemming from the entirety of provincial areas. Regarding the directional spill overs from others, the Balinusra region exhibits the highest directional spill over value among all regions, standing at 79.1973%. Following closely, the Kalimantan region demonstrates the second-highest directional spill overs value, at 79.18247%, succeeded by the Java, Sulawesi, and Sumatra regions, respectively at 79.07210%, 78.94064%, and 76.71235%. Conversely, the Sumatra region manifests the lowest directional spill overs from others, quantified at 76.35867%.

The concept of directional spill overs to others delineates the influence of spill overs disseminated from one province to the entire provincial area. Regarding the value of directional spill overs to others, it can be elucidated that the Java region exhibits the highest value among all regions, standing at 87.50788%. Subsequently, the Balinusra region represents the second-highest directional spill overs value, at 81.89109%, followed by the Sulawesi, Kalimantan, and Sumatra regions, each at 80.67842%, 79.79019%, and 75.84975%, respectively. Conversely, the Mamapapa area reflects the

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lowest area with directional spill overs to others, quantified at 63.74620%.

Net pairwise spillovers denote the disparity between the value of directional spill overs to others and the value of directional spill overs from others, also known as Net directional spill overs. The total spill overs value, situated in the upper-right corner of the spill overs index estimation output table, signifies the cumulative volatility forecast error variance spill overs across the province's sampled area. The formulation for total spill overs is as follows:

$$\frac{\text{total c from others}}{\text{c to others including own}} * 100\% \quad (8)$$

Additionally, according to the estimated output table, the total spill over index amounts to (469.46353/600.00000) =78.24392%. Hence, it can be inferred that, on average, 78.24392% of the forecast error variance across the six provinces in Indonesia was attributed to spillover effects. This total spill over index value indicates a notably high spillover effect across the six provinces throughout the entire sample period.

Dynamic Spill over Index / Rolling-Sample Total Volatility Spill over

The examination of the dynamic spill over index, also referred to as rolling-time total volatility spill over, employs monthly data series of inflation rates. The dataset spans from January 2012 onwards. Visualization of the plotted data (G_index) depicting inflation in Indonesia is presented in Figure 3.

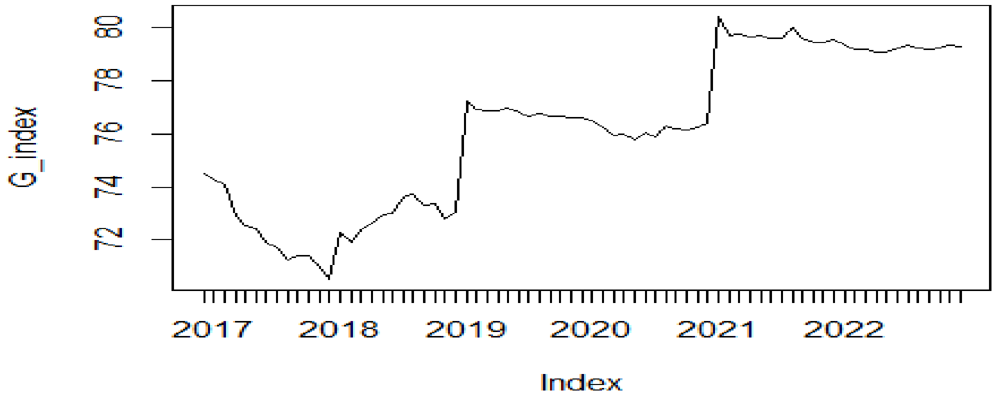

Figure 3: Dynamic Spill over Index / Rolling-Sample Total Volatility Spill over

Figure 3 represents a dynamic process derived from the total spill over index table. Essentially, the outcomes depicted below signify a dynamic progression from the total spill over index table/matrix above, encompassing the total spill over index, directional and pairwise indices, both to and from each region. This portrayal elucidates a single point across the entire period, contrasting with multiple points/periods delineated

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below, reflecting the dynamic nature of the process. The objective is to discern spill overs over time.

The rolling sample total spill over is predicated on the outcomes of the generalized rolling spill over index, grounded in a VAR (1) framework, to ascertain the total spill over index across multiple periods dynamically. Each iteration of the spill over index computation entails the utilization of 60 samples, incrementing by one period. The iterations encompass the entire research sample, comprising 60 samples. In the initial period, the total spill over tends to decline below 72% by 2018, subsequently fluctuating between 74%-76%, and experiencing an overall upsurge to nearly 80% from 2021 to 2022.

The findings of this analysis indicate that during the 2018 period, the inflation rate in Indonesia registered lower levels across all sampled research areas. However, from 2021 to 2022, Indonesian inflation demonstrates a tendency to fluctuate, likely influenced by the repercussions of the Covid-19 pandemic, which commenced towards the end of 2019. In 2022, inflation in Indonesia is anticipated to escalate, with the scarcity of cooking oil identified as one of the contributing factors to this condition.

Directional Volatility Spill Overs

Derived from the output findings of directional volatility spill overs data, the data plot, utilizing Diebold-Yilmaz modelling, is delineated in Figure 4.

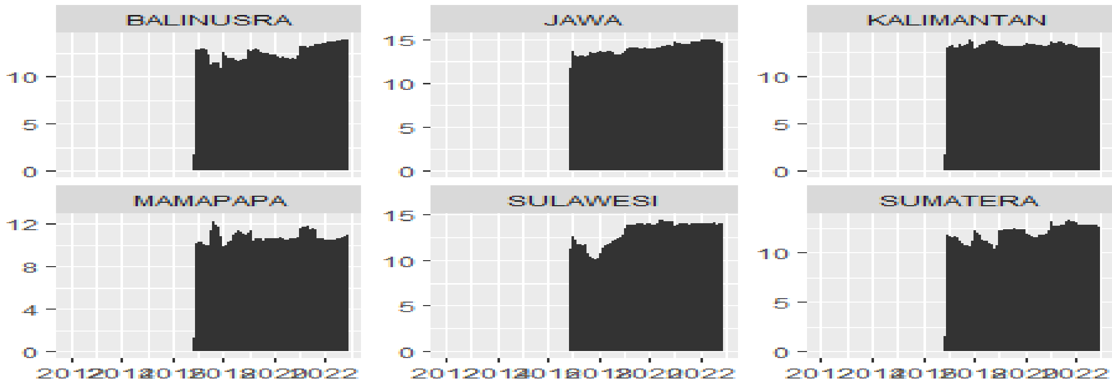

Figure 4: Pattern of Directional Volatility Spill over originating from a Variable.

The graph depicted in Figure 4 showcases the directional spill over patterns from the six regions to one another. It illustrates the overflow dynamics from each region to the entire system collectively. Specifically, the graph highlights the overflow trend originating from the Balinusra region to all other regions (Java, Kalimantan, Mamapapa, Sulawesi, and Sumatra). During the period from 2017 to 2022, the spill

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over from Balinusra to the other regions consistently surpasses 10%, indicating that inflation spill over from the Balinusra region influences more than 10% of inflation in all other regions. Similar overflow patterns are observed in Java and Sulawesi, with intervals of excess inflation ranging from 10-15%. Both Kalimantan and Sumatra also exhibit intervals of excess inflation percentages exceeding 10%. Conversely, in the Mamapapa region, inflation spill over into the fluctuating system reaches 12%.

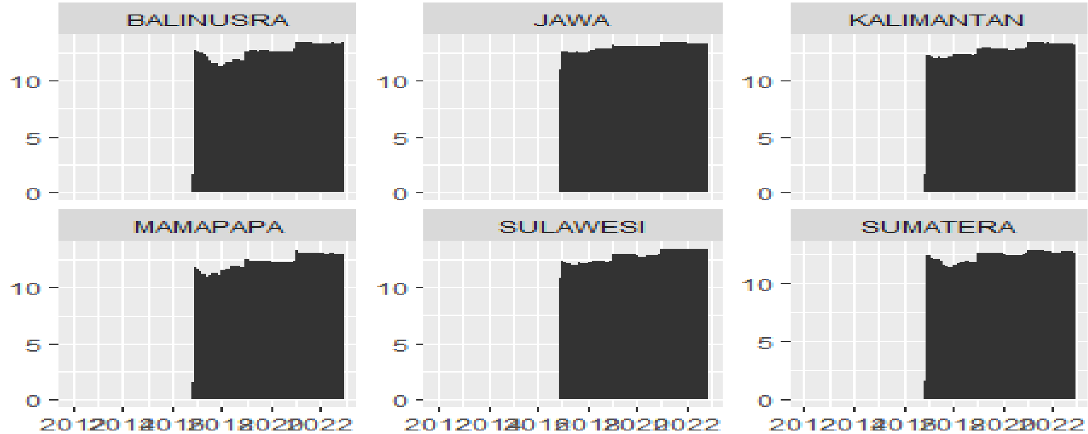

Figure 5: Pattern of Directional Volatility Spill over: to Other Variables

Figure 5 illustrates the directional volatility spill over pattern from the system to each region. The graph indicates that the Balinusra region experiences an inflation spill over from the system, with a percentage exceeding 10%. Similarly, other regions such as Java also exhibit an inflation spill over from the system exceeding 10%. This trend is consistent across various regions. Java, Kalimantan, and Sulawesi demonstrate relatively similar overflow percentages, while Balinusra, Mamapapa, and Sumatra exhibit more fluctuating patterns in overflow percentages.

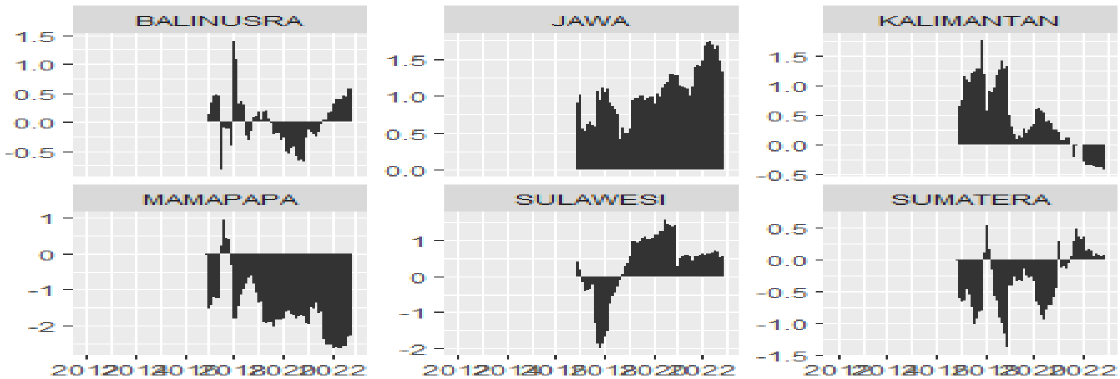

Figure 6: Pattern of Directional Volatility Spill over: Net

Figure 6 illustrates the net pattern of directional volatility spill overs. It reveals that both

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the Balinusra and Sumatra regions exhibit fluctuating net spill overs, indicating periods where they transition between acting as transmitters and receivers, or vice versa. A transmitter region experiences a positive net overflow, while a receiver region shows a negative net overflow. Throughout the entire period, the Java region consistently demonstrates a positive net, establishing itself as a transmitter, signifying that inflation within Java consistently influences other regions. In contrast, the Mamapapa region predominantly functions as a receiver, as indicated by its negative net overflow, suggesting that inflation in Mamapapa is influenced by other regions. Additionally, the Kalimantan region predominantly acts as a transmitter across most periods. Initially, Sulawesi emerges as a receiver due to a significant negative net overflow in the early period, but post-2018, it transitions into a transmitter region with a positive net.

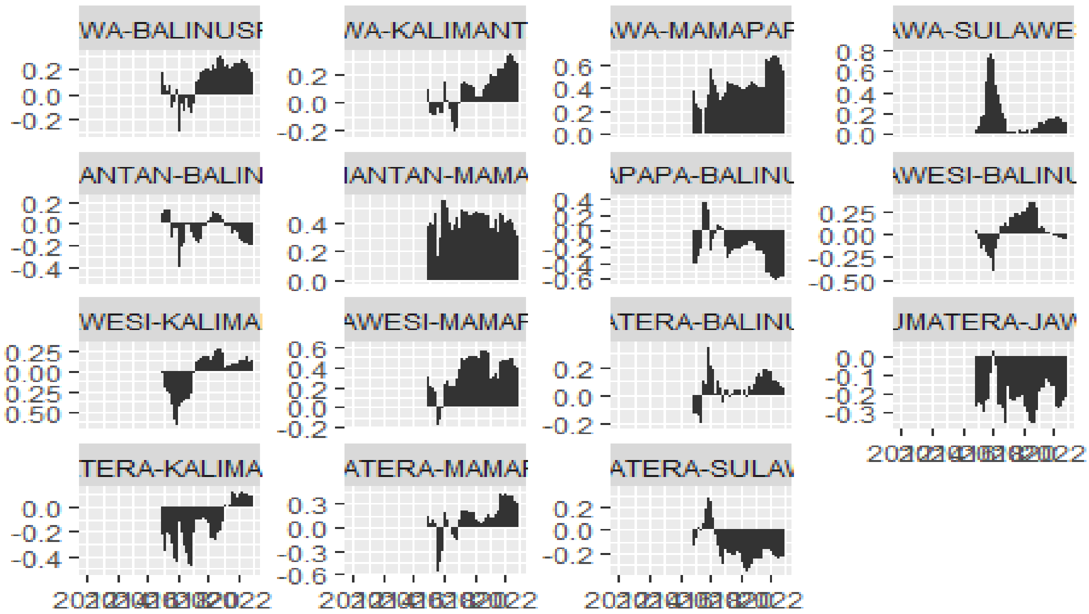

Figure 7: Pattern of Directional Volatility Spill over: Net Pairwise

Figure 7 depicts the pairwise net pattern, illustrating the net relationship between each combination of regional pairs. Notably, pairs such as Java-Mamapapa, Java-Sulawesi, and Kalimantan-Mamapapa exhibit a net positive, indicating that the Java region acts as a transmitter for Mamapapa and Sulawesi, while Kalimantan serves as a transmitter for the Mamapapa region. Conversely, the Sumatra-Java region pair consistently demonstrates a negative net throughout the period, signifying that Sumatra is the recipient of Java. Other pairs exhibit fluctuating nets, transitioning between acting as transmitters and receivers across different periods.

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Visualization of Connectedness Network

The Connectedness Network visualization represents the aggregate spill over index table value, thus elucidating the total spill over index table value through a network graph. Green and purple hues signify positive and negative signs respectively, while the circumference of each node corresponds to the magnitude of the net direction of each province.

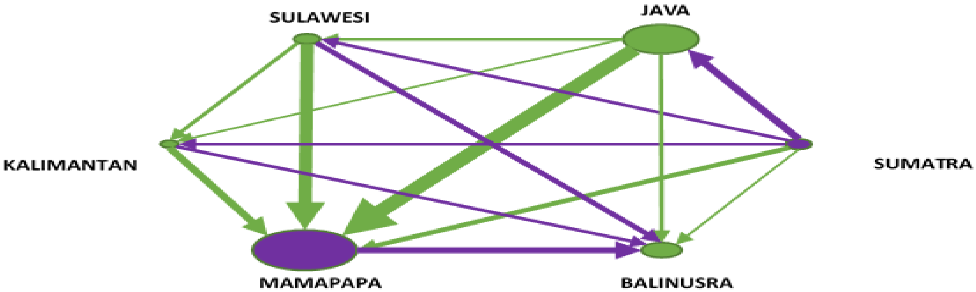

Figure 8: Pattern of Connectedness Network Spill over Inflation in Indonesia

Figure 8 illustrates the connectivity within the Inflation Spill over Network in Indonesia. This network comprises nodes representing provinces such as Java, Sumatra, Kalimantan, Balinusra, and Mamapapa. The connectedness network delineates the extent of proximity, denoted by the size of the nodes, which reflects the overall net spill over. Additionally, the network includes edges, representing directed lines indicating net spill over on individual observations. Green denotes a positive net, while purple signifies a negative net. Moreover, Figure 8 highlights that the provinces acting as transmitters are Java, Sulawesi, Kalimantan, and Balinusra, as indicated by the nodes, whereas Sumatra and Mamapapa function as receivers.

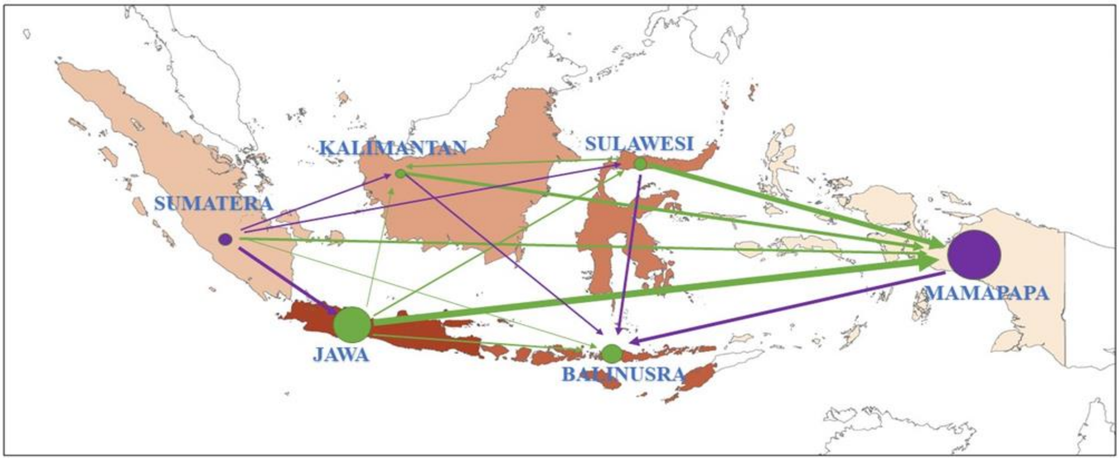

Figure 9: Map of Connectedness Network Spill over Inflation in Indonesia

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The Inflation Connectedness Network in Indonesia, depicted in Figure 9, reveals that all six regions exhibit predominantly positive net spill overs. Java Island emerges as the primary influencer, exerting the largest positive net influence on the other five regions. Conversely, the Mamapapa region demonstrates the highest degree of interconnectedness with the other regions but experiences a net negative spill over, indicating greater susceptibility to external influence. Sumatra also displays significant interconnectivity with other regions, albeit to a lesser extent than Mamapapa.

The Connectedness network analysis reveals that Java Island exerts influence on five other regions: Sulawesi, Kalimantan, Mamapapa, and Balinusra. Java Island exhibits a net positive spillover effect, with the most significant impact observed on the Mamapapa region and the least impact on the Balinusra region.

Conversely, the Sumatra region tends to experience a negative net spill over, indicating that it is more influenced by other regions than it influences them. Sumatra is influenced by Java, Sulawesi, and Kalimantan, while also exerting positive influence on the Balinusra and Mamapapa regions.

In contrast, Balinusra is predominantly influenced by the other five regions, particularly Java. Although the connectivity with other regions tends to be negative, Java and Sumatra still influence Balinusra positively. Similarly, Mamapapa is significantly influenced by the other five regions, except for Balinusra. It emerges as the region most closely associated with the others in terms of network connectivity.

The connectivity analysis shows that Kalimantan has influence over the other four regions, although less than Java. However, Kalimantan's impact is overshadowed by Balinusra, indicated by a negative net. Sulawesi exhibits mixed connectivity: negative with Java and Kalimantan, and positive with Mamapapa and Sumatra.

DISCUSION AND CONCLUSION

Discussion

Examinations into the drivers of national inflation rates must extend beyond monetary aspects to encompass non-fundamental factors. These non-fundamental determinants not only shape headline inflation locally and nationally but also stem from variables like volatile food production and supply disruptions across regions. Interactions among regions, influenced by goods supply dynamics and infrastructural accessibility, underscore the complexity of inflation transmission mechanisms. Addressing these factors is vital for policymakers in setting and sustaining stable national inflation targets. Recommendations emerging from this study highlight the imperative of

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enhancing physical connectivity across Indonesia's western and eastern regions, alongside ensuring consistent access to essential commodities. While this research focuses on Indonesian provinces, future studies could explore the Inflation Connectedness Network across various countries, considering regional data structures and extending the analysis to global comparisons. Researchers are encouraged to incorporate up-to-date data series in their investigations.

Conclusion

This study assesses inflation spillover effects across regions in Indonesia. Analysis of the Net Pairwise Spill overs reveals that self-spill over from Sumatra to Sumatra is most pronounced. Additionally, directional spill overs indicate that Balinusra exhibits the highest values, followed by Kalimantan, Java, Sulawesi, and Sumatra. Directional spill overs to others signify the transmission of spillover effects from one provincial area to the entire region. The sequence of directional spill overs to others is as follows: Java, Balinusra, Sulawesi, Kalimantan, Sumatra, and Mamapapa. The total inflation spill over index in Indonesia amounts to 78.24392%, indicating a substantial spillover effect across the six provinces. Visualization of the Connectedness Network illustrates the total Inflation Spill over Index in Indonesia, highlighting Java, Sulawesi, Kalimantan, and Balinusra as transmitter regions. Conversely, Sumatra and Mamapapa do not serve as transmitter regions. These findings underscore the significant interregional interactions shaping inflation dynamics.

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