Assignment 1: Data Description

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1 Introduction

Economic growth, foreign direct investment (FDI), official development assistance (ODA), and remittances are key channels through which external financial flows influence domestic development. Economists study these variables to understand how international capital movements affect output, investment, and household welfare. Remittances, in particular, stabilize consumption and support growth by providing steady income to households (Burgess and Haksar 2005; Salahuddin and Gow 2015), while FDI and ODA promote productivity and infrastructure development (Dakila and Claveria 2007; Tuaño-Amador et al. 2022). Beyond these direct effects, remittances also influence the *real exchange rate* by increasing demand for domestic goods and services, which can raise local prices relative to foreign prices. This leads to a *real appreciation*, making exports less competitive and imports cheaper—a mechanism often described as a "Dutch disease" effect (Carare et al. 2025). Understanding these channels is essential for assessing how external inflows shape both short-term macroeconomic stability and long-run growth prospects.

2 Data

This analysis uses annual World Development Indicators for the Philippines from 1977 through 2023 (World Bank 2025). The main series used in the paper are: total population, gross domestic product (GDP, current local currency units), net inflows of foreign direct investment (FDI, percent of GDP or level as noted in the figure captions), official development assistance (ODA), and personal remittances.

- **GDP** displays a clear upward trend with notable cyclical downturns and inflection points (for example, around the late 1990s, the 2008–09 global financial shock, and the 2020 pandemic year), suggesting persistent growth combined with episodic shocks that are relevant for impulse-response analysis.

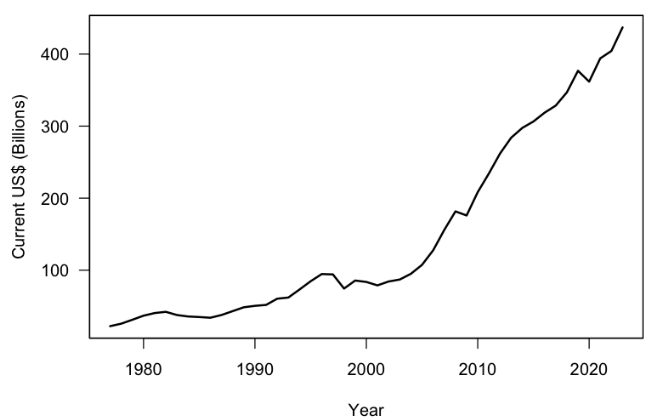

Figure 1: Philippines gross domestic product, 1977–2023

- **FDI** is considerably more volatile than GDP: it exhibits large year-to-year swings, occasional spikes and troughs, and episodes of both comovement and divergence with GDP. This volatility motivates treating capital flows separately and examining their dynamic responses to output disturbances.

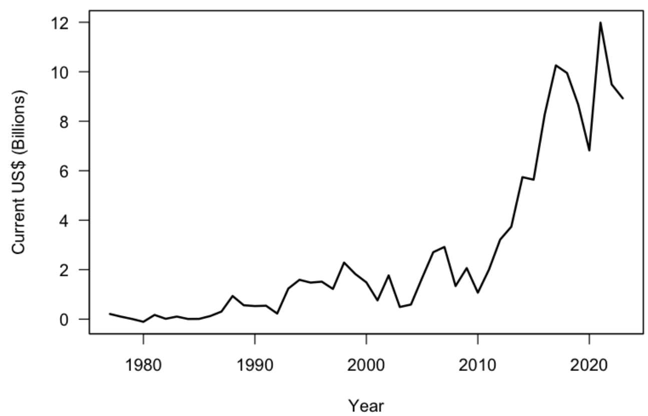

Figure 2: Philippines Foreign direct investment net inflows, 1977–2023

3 Methodology & Results

3.1 Vector Autoregression and Reduced-Form Impulse Response Function

A vector autoregression (VAR) models a set of variables jointly by regressing each variable on its own lags and on the lags of the other variables. Written compactly,

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t,$$

the VAR is a flexible reduced-form framework that summarizes how shocks propagate through a small macroeconomic system without imposing strong structural restrictions. For this application, we use growth rates (to improve stationarity), select the lag order using information criteria (AIC/BIC) and stability diagnostics, estimate each equation by OLS, and compute impulse-response functions (IRFs) up to a 10-year horizon by iterating the estimated companion form forward. Because the reduced-form residuals are contemporaneously correlated, we orthogonalize shocks using a Cholesky decomposition of the residual covariance matrix—placing GDP first so that the reported IRFs describe the dynamic effect of an unexpected GDP shock that can affect other variables within the same year but not vice versa—and quantify uncertainty with bootstrap (or Monte Carlo) confidence bands constructed from repeated re-sampling. Key assumptions include weak stationarity of the transformed series, linearity of dynamics, and that the chosen ordering and lag structure capture the relevant timing. Diagnostics for residual autocorrelation, system stability (eigenvalues), and robustness to alternative orderings are reported elsewhere.

Table 1 reports the VAR coefficients (own- and cross-lag effects and significance), which indicate persistence and short-run predictive links that generate the IRFs.

Table 1: VAR coefficients

	Dependent variable			
	gdp_t	fdi_t	oda_t	$remit_t$
	(1)	(2)	(3)	(4)
c	4.8476^{***}	11.5953	6.779	9.1879^{***}
gdp_{t-1}	0.3812^{**}	3.6881	−2.1692	0.553^{*}
fdi_{t-1}	0.0073	−0.0632	−0.0142	0.0196
oda_{t-1}	0.01	−0.013	0.0071	0.0019
$remit_{t-1}$	−0.1159	−0.4734	0.7426	-0.3189^{*}

Notes. Based on OLS regressions estimated for variables measured in growth rates with left-hand variable in columns (1–4) running from $t = 1977$ to 2023. The symbol * denotes statistical significance at the 10% level, ** at 5%, and *** at 1%.

Table 2 presents the impulse-response function (IRF) point estimates at horizons $h = 0, \ldots, 10$ (along with corresponding uncertainty bands), illustrating both the magnitude and duration of each variable's dynamic response to shocks within the VAR system.

Table 2: Impulse responses

Horizon	$\frac{\partial \mathbb{P}(variable_t \mid 1, \mathbf{y}_{t-h}, \ldots, \mathbf{y}_{t-h-m+1})}{\partial gdp_{t-h}}$		
h	fdi_t (1)	oda_t (2)	$remit_t$ (3)
0	0.0000	0.0000	0.0000
1	3.6881	−2.1692	0.5530
2	0.9389	−0.4839	0.1027
3	0.2170	−0.1280	0.0325
4	0.0575	−0.0298	0.0064
5	0.0133	−0.0078	0.0020
6	0.0035	−0.0018	0.0004
7	0.0008	−0.0005	0.0001
8	0.0002	−0.0001	0.0000
9	0.0001	−0.0000	0.0000
10	0.0000	−0.0000	0.0000

Notes. The symbol * denotes statistical significance at the 10% level, ** at 5%, and *** at 1%.

Figure 4 displays the same impulse-response functions (IRFs) with shaded confidence bands, allowing readers to visually assess the timing, direction, and statistical precision of the estimated dynamic responses.

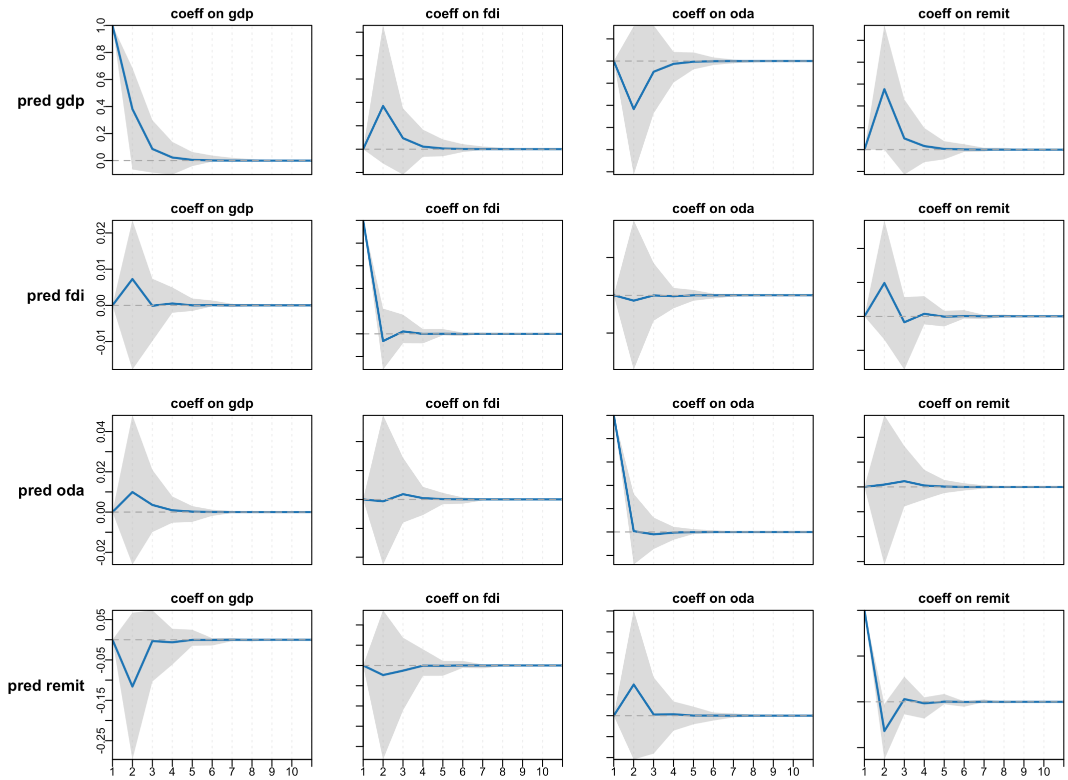

Figure 3: Reduced-form impulse response functions

3.2 Bayesian Methods

Bayesian vector autoregression (BVAR) extends the VAR framework by combining the likelihood from the time-series model with prior beliefs about the coefficients to produce a posterior distribution for all model parameters. Intuitively, the Bayesian approach guards against overfitting in small samples by shrinking coefficient estimates toward sensible values (for example, toward zero for cross-variable lags and toward a random-walk unit for own lags) while still letting the data update those beliefs. Formally, if the reduced-form VAR is $y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t$ with $u_t \sim N(0, \Sigma_u)$, a BVAR specifies a prior $p(c, \{A_i\}, \Sigma_u)$ and computes the posterior $p(c, \{A_i\}, \Sigma_u \mid \text{data}) \propto$

$p(\text{data} \mid c, \{A_i\}, \Sigma_u)\, p(c, \{A_i\}, \Sigma_u)$. The posterior neatly summarizes parameter uncertainty and leads directly to posterior predictive distributions and credible intervals for impulse responses.

We use a Minnesota-style prior (tight shrinkage on cross-coefficients, looser on own lags) because our annual sample is modest relative to the number of parameters. Key implementation details are: (1) data are expressed in growth rates as in the frequentist VAR; (2) lag length is chosen by information criteria and stability diagnostics before estimating the BVAR; (3) the overall tightness and relative shrinkage hyperparameters are selected by empirical rules and checked for sensitivity; (4) posterior draws are obtained via the conjugate posterior or MCMC sampling (several thousand retained draws after burn-in) and monitored for convergence; (5) for each posterior draw we compute orthogonalized impulse responses using the same Cholesky ordering as the reduced-form VAR (GDP first) so that Bayesian IRFs are directly comparable to the frequentist IRFs; and (6) credible bands are formed by taking quantiles of the IRFs across posterior draws (for example, the 2.5th and 97.5th percentiles for 95

The BVAR differs from the OLS VAR primarily through shrinkage: it reduces sampling variance (smoother IRFs and narrower bands) while allowing the data to dominate where information is strong. We report posterior diagnostics (trace plots, effective sample sizes) and stability checks for the companion matrix across draws to ensure robustness.Table 3 presents posterior summaries for coefficients and related quantities (posterior mean, median, posterior standard deviation, credible intervals, and the posterior probability a coefficient exceeds zero).

Table 3: Bayesian VAR posterior estimates

	Regressor	Mean	Median	SD	95% CI	Pr(>0)
gdp	c	5.8268	5.8705	7.7360	(-10.9691, 22.3860)	0.826
	gdp_{t-1}	0.0633	0.0461	0.3873	(-0.6973, 0.8871)	0.573
	fdi_{t-1}	0.0059	0.0068	0.0610	(-0.1207, 0.1273)	0.559
	oda_{t-1}	0.0061	0.0056	0.0873	(-0.1708, 0.1934)	0.533
	$remit_{t-1}$	-0.0060	-0.0060	0.2779	(-0.5987, 0.5767)	0.487
fdi	c	24.7618	25.1260	24.8179	(-24.8435, 72.9350)	0.846
	gdp_{t-1}	0.6678	0.5969	1.1714	(-1.5024, 3.2808)	0.726
	fdi_{t-1}	-0.0731	-0.0669	0.1850	(-0.4585, 0.2805)	0.337
	oda_{t-1}	-0.0574	-0.0549	0.2716	(-0.5767, 0.4718)	0.425
	$remit_{t-1}$	0.1709	0.1428	0.8528	(-1.4917, 1.9563)	0.575
oda	c	1.6545	1.7411	13.4065	(-24.4169, 28.8696)	0.556
	gdp_{t-1}	-0.3126	-0.2920	0.6313	(-1.6802, 0.8777)	0.303
	fdi_{t-1}	-0.0057	-0.0094	0.0992	(-0.1900, 0.1945)	0.469
	oda_{t-1}	0.0297	0.0274	0.1427	(-0.2519, 0.3105)	0.585
	$remit_{t-1}$	0.0567	0.0571	0.4668	(-0.8339, 1.0104)	0.547
remit	c	9.7121	9.7446	2.2303	(5.3855, 14.1349)	1.000
	gdp_{t-1}	0.0653	0.0583	0.1072	(-0.1287, 0.3077)	0.740
	fdi_{t-1}	0.0166	0.0163	0.0166	(-0.0157, 0.0501)	0.856
	oda_{t-1}	-0.0049	-0.0046	0.0234	(-0.0503, 0.0423)	0.416
	$remit_{t-1}$	-0.0716	-0.0682	0.0812	(-0.2418, 0.0774)	0.189

3.3 Stationarity and Structural Breaks

Stationarity and structural breaks are central for time-series inference because nonstationary data or unmodeled breaks can produce spurious relationships and misleading impulse responses. We therefore apply both unit-root tests and endogenous break-detection methods and report summaries in Table 4.

Unit-root testing. We use two complementary tests for stationarity: the augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. These tests have opposite null hypotheses, which helps guard against misleading conclusions when one test alone is inconclusive. The ADF test has the null of a unit root (nonstationarity) and the alternative of stationarity; we estimate the ADF regression with an intercept and, where appropriate, a deterministic time trend and select the lag length via information criteria (AIC/BIC) and practical residual diagnostics. The KPSS test has the null of stationarity and the alternative of a unit root (or trend-stationarity depending on the chosen specification); we report KPSS statistics using a Newey–West bandwidth chosen by the usual automatic selection rules. When the ADF fails to reject and the KPSS rejects the null of stationarity, the indicators together provide evidence consistent with nonstationarity; when ADF rejects and KPSS does not, we interpret that as evidence in favor of stationarity.

Structural-break detection. Standard unit-root tests can be biased in the presence of structural breaks, so we complement them with break-aware procedures. We apply the Zivot–Andrews test to allow a single endogenously determined structural break in either the level or trend; for multiple breaks we use the Bai–Perron approach implemented via the ‘strucchange::breakpoints‘ routine, setting a trimming parameter (commonly 0.10–0.15 of the sample) and selecting the number of breaks with BIC and sequential F-tests. For each detected break we report the estimated break years in Table 4. Implementation is done in R using ‘urca::ur.df‘ for ADF variants, ‘tseries::kpss.test‘ for KPSS, ‘urca‘ or the ‘zoo‘/‘urca‘ implementations for Zivot–Andrews, and ‘strucchange::breakpoints‘ for multiple break detection; all test choices and tuning parameters are recorded in the code used to generate the output.

Why these choices matter for the VAR. VAR estimation and the validity of impulse responses rely on (weak) stationarity of the series. Nonstationary series can cause biased parameter estimates and invalid asymptotic inference. When variables are I(1) but cointegrated, a vector error-correction model (VECM) is the appropriate representation; when series are nonstationary without cointegration, first-differencing removes stochastic trends but also changes the interpretation of coefficients (short-run dynamics rather than levels). Structural breaks — for example large policy shifts or crisis years — can mimic nonstationarity or produce shifts in dynamics; if breaks are present we either include break dummies, estimate the VAR over sub-samples, or use methods that allow for time-varying parameters as a robustness check. In this paper, because the main flow variables are analyzed in growth rates (log differences) and because break tests identify only a small number of discrete breaks, our primary VAR specifications use growth rates while we report break years and run robustness specifications that include break dummies or split-sample estimations when appropriate.

Table 4 summarizes test statistics and break dates: ADF statistic and p-value, KPSS statistic and p-value, the number of Bai–Perron breaks found, and the estimated break years. For a non-specialist, the practical guidance is: (i) if ADF indicates stationarity and KPSS does not reject stationarity, we proceed with level-based analysis; (ii) if ADF fails to reject a unit root while KPSS rejects stationarity, we treat the series as nonstationary and work with differences (or investigate cointegration); and (iii) if breaks are detected in Table 4, we examine whether including break dummies or estimating separate regimes changes the estimated IRFs materially — if so, the results are reported as robustness checks in the accompanying output.

Table 4: Testing of stationarity and structural breaks

ggdp	-3.7955	0.028	0.0516	0.100	0	NA
gfdi	-10.1907	0.010	0.2426	0.100	0	NA
goda	-3.7237	0.034	0.1246	0.100	0	NA
gremit	-3.5273	0.049	0.3420	0.100	0	NA

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