Assignment 1: Data Description

Charlene R. Ramos

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1 Introduction

External financial flows such as foreign direct investment (FDI), official development assistance (ODA), and personal remittances are central to understanding how outside funding advances development in the Philippines. As an emerging economy, the Philippines depends on these inflows to finance investment, create employment opportunities, and support household welfare. Each channel affects the economy through distinct but interconnected mechanisms:

1. FDI expands productive capacity and facilitates technology transfer;
2. ODA supports infrastructure and strengthens institutions; and,
3. Remittances raise household income, stimulating consumption and reducing poverty.

(Burgess and Haksar 2005; Salahuddin and Gow 2015; Dakila and Claveria 2007; Tuaño-Amador et al. 2022)

Beyond these direct effects, remittances exert broader macroeconomic influence through the real exchange rate. As remittance inflows increase domestic purchasing power, demand for non-tradable goods and services elevates relative to tradables, driving up local prices. This can make exports less attractive and shift resources toward non-tradable sectors—a dynamic described as the "Dutch disease" effect (Carare et al. 2025). For a developing economy like the Philippines, which balances competitiveness in export-oriented sectors with reliance on external income sources, understanding these tradeoffs is crucial for evaluating short-term growth and long-run prosperity.

2 Data

This analysis uses annual data from the World Bank's Development Indicators on the Philippines from 1977 through 2023 (World Bank 2025). The series of interest are:

- Total population
- Gross domestic product (GDP)
- Net inflows of foreign direct investment (FDI)
- Official development assistance (ODA)
- Personal remittances

Population. Although the Philippines continues to experience positive population growth, the rate of increase has declined steadily over the past several decades. This demographic transition reflects broader structural changes in the economy and society. Fertility rates have fallen due to greater access to education, women's labor force participation, and the expansion of family planning programs. Rising living costs and changing social norms in urban areas have further reinforced preferences for smaller families. International migration has also moderated domestic population growth, as many working-age Filipinos delay or limit childbearing while employed abroad.

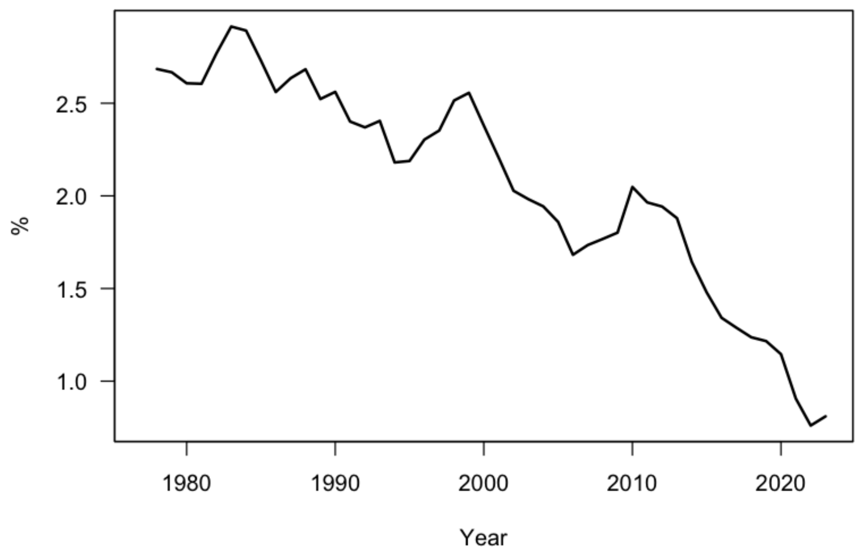

Figure 1: Population growth rate, 1977–2023

GDP. The inconsistent trend highlights the sensitivity of Philippine income growth to external shocks (Asian Financial Crisis, Great Recession, and COVID-19) as well as political (i.e., weak governance and corruption) and structural factors (e.g., high income inequality and large informal sector). However, the recurring rebounds demonstrate a degree of economic resilience supported by remittances, service-sector expansion, and macroeconomic reforms over time.

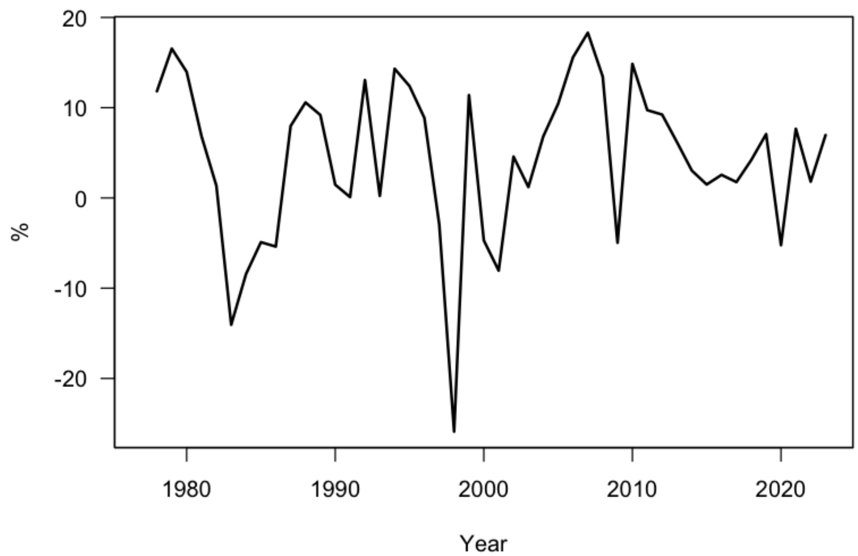

Figure 2: Per-capita GDP growth rate, 1977–2023

FDI and ODA. The annual growth rates of FDI and ODA as percentages of GDP are also highly erratic. FDI exhibits sharp year-to-year swings, including a major surge in the 1980s and contractions during periods of uncertainty, such as in 2008–2009. ODA flows are more stable but exhibit moderate fluctuations linked to project cycles, donor priorities, and international conditions. Overall, FDI displays greater short-term volatility, while ODA reflects steadier, policy-driven financing patterns. This motivates treating capital flows separately when examining their dynamic responses to output disturbances.

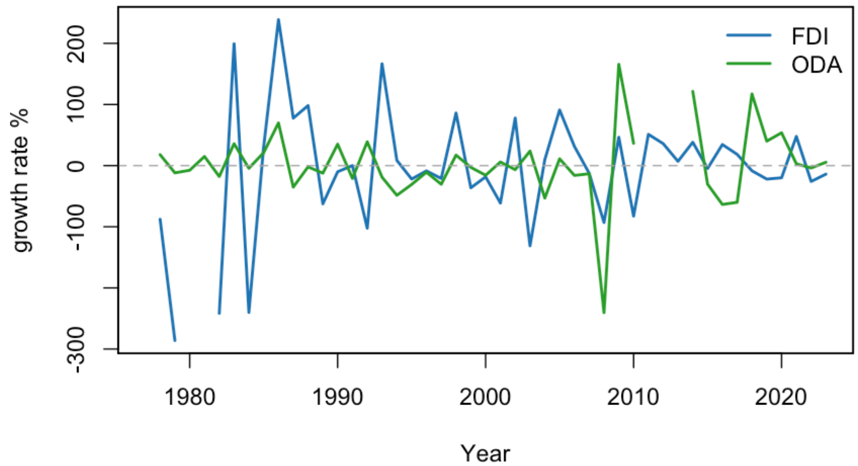

Figure 3: External financial flows as percentage of GDP, 1977–2023

3 Methodology & Results

3.1 Vector Autoregression and Reduced-Form Impulse Response Function

A vector autoregression (VAR) is a statistical model of the joint dynamics among multiple time-series variables without presuming a specific causal structure. In a VAR, each variable is expressed as a linear function of its own past values and the past values of all other variables in the system. Formally, the model can be written as

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t,$$

where y_t is a vector of endogenous variables, A_i are coefficient matrices capturing lagged relationships, c is a vector of intercepts, and u_t is a vector of innovations or shocks. This specification allows the data to reveal how variables interact dynamically over time, with minimal theoretical restrictions on the direction or magnitude of effects.

The VAR approach is particularly well suited for macroeconomic applications when theory may not specify exact relationships between variables. It provides a reduced-form representation that quantifies how shocks to one variable influence others over subsequent periods. In this study, the VAR helps identify how disturbances in foreign direct investment (FDI), official development assistance (ODA), and remittances transmit to GDP growth over a multi-year horizon. The main assumptions underlying the VAR include weak stationarity of the transformed data, linearity of relationships among variables, and correct specification of lag length and ordering. When these conditions are satisfied, the VAR offers a powerful yet flexible empirical framework for examining the propogation of macroeconomic shocks and the temporal linkages among key economic variables.

Implementation proceeds in several steps. First, the time-series data are transformed into growth rates (log differences) to improve stationarity, ensuring that the mean and variances of each series remain constant over time. The appropriate lag length (p) is selected using information criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). From there, each equation in the system is estimated by ordinary least squares (OLS). Impulse-response functions (IRFs) are then derived from the estimated VAR to trace the dynamic effect of one-time shocks on the system's variables. These responses are computed by iterating the VAR forward over a 10-year horizon. Uncertainty in the estimated IRFs is quantified through bootstrap or Monte Carlo simulations, which generate confidence bands based on repeated resampling of the estimated residuals. These procedures account for sampling variability and small-sample bias, offering a more reliable measure of the precision of dynamic effects.

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. The VAR results suggest that GDP growth is persistent, meaning past growth tends to carry forward into the next period. Remittances respond positively to past GDP, indicating they rise when the domestic economy strengthens, but also demonstrate slight mean reversion. In contrast, FDI and ODA appear largely unaffected by recent domestic conditions, implying these flows are driven more by external or structural factors than by short-term economic dynamics.

Table 1: VAR coefficients

	Dependent variable			
	gdp_t (1)	fdi_t (2)	oda_t (3)	$remit_t$ (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. 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 $h = 0, \ldots, 10$, illustrating both the magnitude and duration of each variable's dynamic response to shocks within the VAR system. The external flows can be interpreted as drivers (or transmitters) of shocks that influence GDP growth over time. When these variables affect GDP in subsequent periods, it reveals how external capital inflows contribute to or dampen domestic economic activity. The results indicate that GDP responds most strongly to FDI shocks, implying that foreign investment inflows have a meaningful and immediate impact on economic growth. Remittances exert a smaller but persistent positive effect, suggesting they help support household income and consumption but do not strongly drive aggregate growth. ODA, on the other hand, exhibits weak or negative responses, indicating that aid flows may not translate efficiently into short-run growth, possibly due to implementation delays or targeting inefficiencies.

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

Figure 4 displays the same impulse-response functions (IRFs) with shaded confidence bands, which permits visual assessessment of the timing, direction, and statistical precision of the estimated dynamic responses. In summary, external flows matter for GDP primarily through FDI, which fuels short-run growth dynamics, while remittances provide steady, modest support and ODA appears less effective as a growth stimulus.

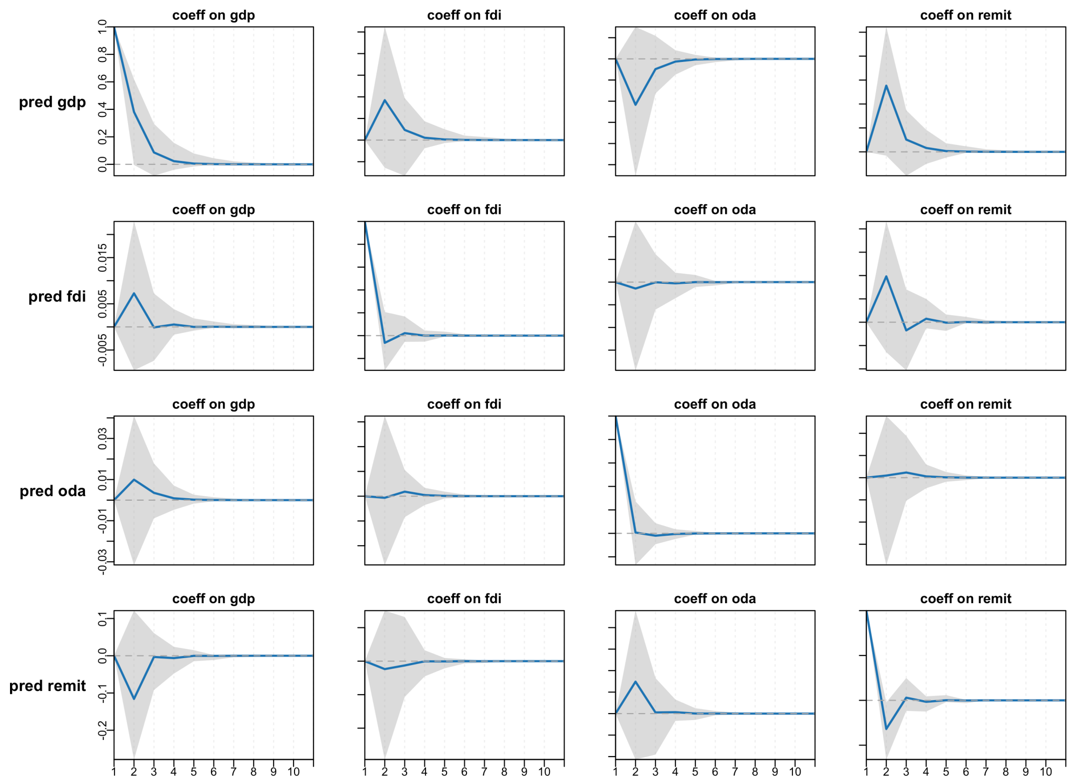

Figure 4: Reduced-form impulse response functions

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. A BVAR specifies a prior and computes the posterior, which neatly summarizes parameter uncertainty and leads directly to 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 VAR;
2. Lag length is chosen by information criteria before estimating the BVAR;
3. Posterior draws are obtained via the conjugate posterior or MCMC sampling (several thousand retained draws after burn-in) and monitored for convergence;
4. For each posterior draw, we compute orthogonalized impulse responses using Cholesky ordering (GDP first); and,
5. Credible bands are formed by taking quantiles of the IRFs across posterior draws.

The BVAR differs from the VAR primarily through shrinkage: it reduces sampling variance (smoother IRFs and narrower bands) while allowing the data to dominate where information is strong. 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 as summarized 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. The KPSS test has the null of stationarity and the alternative of a unit root. 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 a break-aware procedure. We use the Bai–Perron approach implemented via the ‘strucchange::breakpoints‘ routine in R. For each detected break, we report the estimated break years in Table 4.

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 since break tests do not identify any breaks, our primary VAR specifications use growth rates.

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. 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.

Table 4: Stationarity tests and structural breaks

Variable	ADF stat	ADF p-val	KPSS stat	KPSS p-val	Breaks	Break years
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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