Exploring the Impact of Economic Policy Uncertainty on Foreign Direct Investment Flows

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Executive Summary

This paper explores the impact of both country-level and global Economic Policy Uncertainty (EPU) on Foreign Direct Investment (FDI) inflows in OECD member countries. This research is relevant for government policymakers because FDI brings a range of economic benefits to host countries, as outlined in this paper's introduction. We hypothesise that greater country-level EPU (CEPU) and global EPU (GEPU) negatively impact FDI inflows. To address this hypothesis, we construct a panel dataset of all 38 OECD member countries for the years 2000-2022 inclusive, and control for other macroeconomic factors, such as existing FDI stock and GDP growth rates. In line with existing literature, we also implement a lag between macroeconomic factors and observed FDI inflows for most models. Our findings indicate that increases in both GEPU and CEPU are associated with lower FDI inflows. For only statistically significant coefficients, a 1% increase in GEPU is associated with a 0.45% decrease in FDI inflows, and a 1% increase in CEPU is associated with a 0.40% to 0.49% decrease in FDI inflows. These findings support our hypothesis of a negative and statistically significant relationship between both GEPU and CEPU and FDI inflows. However, while coefficient estimates of GEPU and CEPU were consistent across model specifications, model robustness checks indicated potential multicollinearity issues, which could have impacted the reliability of coefficient estimates.

AI Statement

I acknowledge the use of generative AI in *literature search* in this paper. However, the work reported remains my own.

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1. Introduction

This paper examines the effects of Economic Policy Uncertainty (EPU), at both the country-level (CEPU) and global-level (GEPU), on Foreign Direct Investment (FDI) inflows (as a percent of GDP) in OECD countries. FDI is defined as "*the net inflows of investment to acquire a lasting management interest… in an enterprise operating in an economy other than that of the investor*" (World Bank Group, 2025).

This analysis has two primary applications. Firstly, there is a policy-prioritisation angle. Many OECD governments commit significant resource to attracting and retaining FDI, such as through tax and non-tax incentives, and special economic zones (OECD, 2022, p. 37). This research provides a foundation for governments to better contextualise observed changes in exogenous macroeconomic factors when evaluating how government policies impact FDI inflows.

Secondly, this analysis could support further economic research by government agencies. The scale and direction of the coefficients produced in this analysis could inform forecasting models of FDI inflows, and inference of the macroeconomic factors and conditions which best support FDI. Additionally, this analysis could improve understanding of the expected impact of a change in policymaking or governance on expected EPU, and by extension on expected FDI inflows.

Attracting and retaining FDI is important for a variety of reasons. Firstly, meta-regression analysis such as Bruno et. al. (2018) finds that FDI positively impacts economic growth. Additionally, investment from foreign owned firms can increase wage rates in the host country (Lipsey, 2002), and foreign institutional ownership can increase a firm's innovative output (Luong et. al., 2017). Foreign owned firms are often more productive than domestic firms (Lipsey, 2002), although research such as Aitken and Harrison (1999) finds the net effect of FDI on productivity to be small, due to a negative offsetting effect of foreign investment on domestic firm productivity.

The evidence base is mixed regarding the theoretical relationship between uncertainty and investment. Some research suggests that uncertainty reduces investment, other research that it increases the economic benefit of waiting to invest, leading to delayed investment. Some research even suggests that, under certain conditions, increased uncertainty could increase investment.

The empirical section of the literature review was more FDI-specific and generally, but not exclusively, suggested a negative relationship between uncertainty and FDI. Therefore, our null hypothesis is that uncertainty is negatively associated with FDI.

We start with an Ordinary Least Squares (OLS) model, in line with much of the existing literature. OLS modelling is simple to implement and interpret, and therefore useful for testing potential model features, such as lagged independent variables. We then test alternative Fixed Effects and Random Effects specifications, to see if this helps to control for time-invariant effects and improve the robustness of coefficient estimates. Finally, we test a novel set of instrumental variables using Two-Stage Least Squares modelling, to attempt to control for endogeneity issues.

We then perform diagnostic tests, model robustness checks, and discuss both research limitations and conclusions. Focussing on only statistically significant parameter estimates, we find that a 1% increase in GEPU is associated with a 0.45% decrease in FDI inflows, and that a 1% increase in CEPU is associated with between a 0.40% and 0.49% decrease in FDI inflows. Both findings were OECD-specific, but broadly aligned with comparable empirical literature where a different panel of countries was used.

However, these results were subject to limitations and caveats. Data coverage for the CEPU variable was around 39.5%, representing full coverage for fifteen of 38 OECD member countries between 2000 and 2022. This could potentially bias the coefficient estimates towards those OECD member countries where data was available. Additionally, we identified potential multicollinearity issues when estimating both CEPU and GEPU simultaneously. Finally, while we identified potential alternative instrumental variables to the existing 'exogenous election timing' dummy variable, future research might compare the relative performance of both the traditional and novel instrumental variables.

2. Literature Review

2.1 Theoretical Background

The theoretical relationship between uncertainty and investment takes a distinctly microeconomic viewpoint, focussing mostly on factors which influence investment decision-making by individual economic actors.

Keynes (1936) suggests that a large proportion of positive economic activity (such as investment) depends more on behavioural factors such as 'spontaneous optimism' than 'mathematical expectation'. This suggests that factors which undermine this 'spontaneous optimism', such as increased uncertainty, may lead to a reduction in 'positive activities' such as investment.

Hicks (1939) constructed a more rational framing of the relationship between uncertainty and investment. He proposed that increasing uncertainty reduces expectations of the future profitability of potential investments, and by extension decreases investment demand.

Bernanke's (1983) paper *Irreversibility, Uncertainty, and Cyclical Investment* suggested that changes in uncertainty can change both the timing of investment projects and whether a firm chooses to invest. When projects are irreversible, greater uncertainty increases the benefit of waiting for further information relative to the benefit of additional returns due to early investment. Firms must then re-assess whether to invest now, or to delay investment. This is important as it adds a new dimension to our thinking on firm investment decision-making: if an investment proposition may be beneficial to the firm, but high economic uncertainty hinders investment at time t, firms can also re-assess the investment proposition at time $t+n$.

Dixit and Pindyck (1994) later expanded on this perspective, terming the economic benefit of waiting for further information the 'option value of waiting'. They suggested that when investment is irreversible and uncertainty is present, the threshold for triggering an investment is higher than simply the cost of capital, and that this threshold increases as uncertainty increases.

Some academics have reached the inverse conclusion. Using a homogenous production function of degree one, and assuming that prices are random in each period, Hartman (1972) found that price and cost uncertainty lead to greater investment if the production function is linearly homogeneous, but indeterminate otherwise. Abel (1983), citing previous research by both Hartman (1972) and Pindyck (1982), and using Pindyck's generalised investment model, found that for both Hartman's discrete-time model and Pindyck's continuous-time model, increased price uncertainty leads to greater firm investment.

Unfortunately, theoretical literature on this topic does not distinguish between how effects might vary for country and global-level EPU. However, in the next subsection, we examine empirical evidence on this topic, which makes this distinction.

2.2 Empirical Evidence

We now consider empirical evidence regarding the relationship between uncertainty and FDI inflows (rather than broad investment, as in the previous section). This subsection takes a more macroeconomic perspective, focussing not on firm-level investment decision-making, but instead on country-level FDI inflows.

Much of the existing literature on uncertainty and FDI either applies to a specific country or all nations where data was available. Additionally, the use of an 'exogenous election dummy', to signify whether an election was held in a given country and year that was not called at the discretion of the government, is hegemonic throughout the literature.

We test an experimental set of instrumental variables in this paper, informed by both economic reasoning and academic literature. The inclusion of stock market volatility (VIX, SPV) was partly inspired by Bloom (2009), gold prices (GLD) by Tansuchat et. al. (2023), and exchange rate volatility (EMV, ERVX) by Korley and Giouvris (2023).

Furthermore, there is strong precedent in existing literature for implementing lagged independent variables. The economic theory underpinning this relates to a hypothesised delay between firms deciding to invest in a country, and that particular investment 'landing' (Mathew, et al., 2021). Also popular is ARDL (Autoregressive Distributed Lag) modelling, which differentiates between the short and long-run effect of uncertainty on FDI, as seen in Haque et. al. (2022), Nguyen and Lee (2021), and Smith (2021).

While some empirical studies we reviewed discussed potential variable endogeneity, and some did use instrumental variables, only one study we reviewed (Nguyen & Lee, 2021) explicitly scanned for potential endogeneity in predictor variables using Granger-causality testing. We implement this approach for this paper; future econometric researchers might also wish to consider its implementation.

Popular control variables in existing literature include GDP growth, GDP per capita, trade openness, financial development, and existing FDI stock. We include the three most popular control variables in this paper, namely FDI stock (FDI_s), GDP growth (GDPg), and GDP per capita (GDPc).

Starting with FDI_s, Jardet et. al. (2023, p. 867) find that FDI_s has a positive and statistically significant impact on FDI inflows (FDI_i).

Next, literature suggests a generally positive and statistically significant relationship between GDPg and FDI_i, such as Nguyen and Lee (2021, p. 5), Haque et. al. (2022, p. 13), Jardet et. al. (2023, p. 867), and Julio and Yook (2016, p. 44). Choi et. al. (2020, p. 42) did derive negative coefficients between GDPg and FDI_i, however these results were not statistically significant.

Results for GDPc were mixed. Papers such as Choi et. al. (2020, p. 39) find a positive and statistically significant relationship between GDPc and FDI_i. Papers such as Jardet et. al. (2023, p. 867) find a negative relationship for advanced and emerging economies, and a positive relationship for developing economies, however neither finding was statistically significant.

Therefore, existing empirical literature is broadly suggestive of a positive relationship between both FDI_s and GDPg with FDI_i, but shows mixed findings regarding the relationship between GDPc with FDI_i. These findings are compared to our own modelling results later in this paper.

There is precedent for log-scaling GDPc, which is often positively skewed, leading to biased coefficient estimates. References to 'log-scaling' in this paper describe a 'natural' log transformation with base $e \approx 2.718$. This practice is used in research such as Choi et. al. (2020), and Jardet et. al. (2023), as well as being well-documented practice in academic textbooks. We test both linear-linear and log-log specifications, as the latter can reduce the impact of outliers on coefficient estimates and simplify coefficient interpretation (Wooldridge, 2006, pp. 197-198).

Like Nguyen and Lee (2021), we test for potential endogeneity (both simultaneity and reverse-causality) issues between dependent and independent variables.

There is a wide variety of empirical literature suggesting a negative relationship between uncertainty and FDI inflows. Studies such as Julio and Yook (2016), Nguyen and Lee (2021), and Choi et. al. (2020) find that CEPU reduces FDI inflows. Additionally, studies such as Smith (2021, p. 12), Noviyanti et. al. (2023, p. 136), and Jardet et. al. (2023, p. 867) find a negative and statistically significant relationship between GEPU and FDI inflows. Aizenman and Marion (1999) also find the negative effect of uncertainty on private investment to be stronger in developing countries.

Country-level studies have identified negative relationships between uncertainty and FDI into France (Smith, 2021), into Indonesia (Noviyanti et. al., 2023), and from the US (Julio & Yook, 2016). Similar findings have been established for global panel datasets such as Jardet et. al. (2023) and Nguyen and Lee (2021), which have examined the effect of uncertainty on FDI inflows both by a country's stage of economic development and overall. Haque et. al. (2022) produced similar analysis for high-income nations, and Choi et. al. (2020) for sixteen OECD nations using OECD bilateral FDI data. However, based on the available literature, this paper is the first to produce these estimates specifically across all 38 OECD member countries.

For CEPU, studies with comparable modelling approaches estimate that the long-run effect of CEPU on FDI_i ranges from (-)0.69 to (-)0.25, and from (-)0.69 to (-)0.67 amongst only statistically significant estimates (Nguyen & Lee, 2021). The panel used in that research included 116 countries at a range of stages of economic development.

For GEPU, in the long run, a 1% increase in global uncertainty leads to a 0.39% decrease in FDI (Haque et. al., 2022). The panel used in that research included nineteen high-income countries. However, one caveat here is that while this paper uses broadly similar model specifications to the studies listed above, both papers used a different modelling approach (ARDL) to this research.

3. Data and Methodology

3.1 Data Sources

To assess the impact of changes in EPU on FDI inflows, we construct a panel dataset of all 38 OECD member countries between 2000 and 2022. A panel of OECD members was selected due to the relatively comprehensive coverage of economic data amongst OECD members, and the goal of focussing on a specific region or group of countries for this analysis. This was important as the literature review suggested that the effects of EPU on FDI inflows vary by a country's stage of economic development.

This study only covers 2000 to 2022, as data coverage was significantly poorer for some variables outside of these years. Due to time limitations, data collection for this research was finished around November 2024, which meant that data for 2023 onwards had not yet been published for all variables. It is important to contextualise these time and regional limitations when interpreting model results.

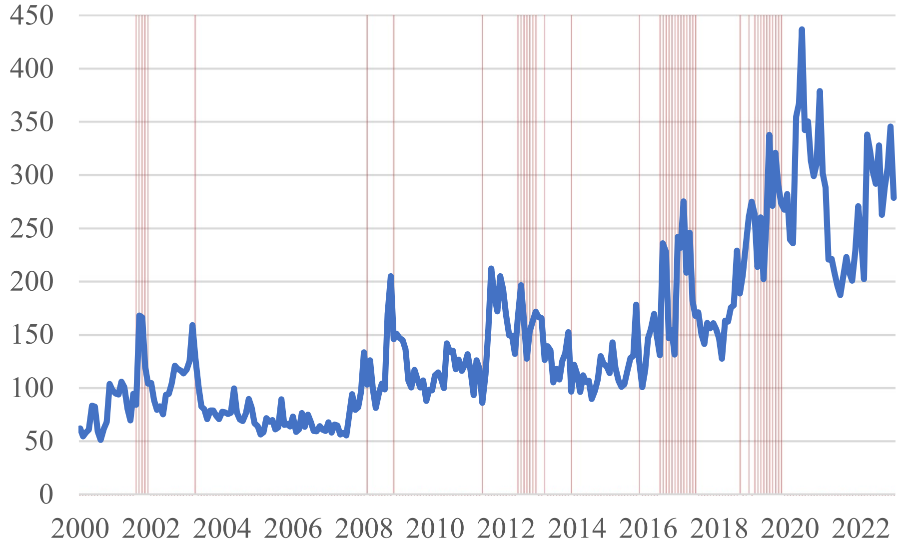
We use Baker et. al.'s (2016) EPU data to measure uncertainty at the country and global level. Data sources for the dependent, control, and instrumental variables include the World Bank, OECD, and Chicago Board Options Exchange.

All models were constructed using Gretl's script functionality, meaning that all use Heteroscedasticity and Autocorrelation-Consistent (HAC) robust standard errors as default. All statistical testing was completed using R and Gretl. Summary statistics were compiled using Excel.

Figure 1: List of Variables

Variable Name	Variable Definition	Source	Category
$FDI\_i_{i,t}$	Foreign direct investment, net inflows (% of GDP)	World Bank, FDI Net Inflows	Dependent Variable
$FDI\_s_{i,t-l}$	Foreign direct investment, total position (% of GDP)	OECD, FDI Stock	Control Variable
$GDPc_{i,t-l}$	GDP per capita (2015 PPP-adjusted US$)	OECD, GDP Per Capita	
$GDPg_{i,t-l}$	Real GDP growth (year-on-year %)	OECD, Real GDP Growth	
$CEPU_{i,t-l}$	Country-level economic policy uncertainty	Baker et. al (2016), Economic Policy Uncertainty Index	Independent Variable
$GEPU_{t-l}$	Global economic policy uncertainty (PPP-adjusted)		
VIX_{t-l}	US equity market volatility	Chicago Board Options Exchange, VIX Index	Instrumental Variable
$SPV_{i,t-l}$	Stock price volatility	World Bank, Stock Price Volatility	
GLD_{t-l}	Global Gold Prices	gold.org, Global Gold Prices	
$ERVX_{t-l}$	Global Exchange Rate Volatility	Chicago Board Options Exchange, CBOE ERVX	
EMV_{t-l}	Exchange Rate Volatility in Equity Markets	Federal Reserve Bank of St. Louis, FRED	

Figure 2: Global Economic Policy Uncertainty, 2000 to 2022, monthly data, PPP-adjusted (bars represent periods of high GEPU volatility)



When examining Global Economic Policy Uncertainty (GEPU), we can see that the data captures the EPU associated with some of the most significant geopolitical economic events between 2000 and 2022. For instance, we can see significant increases in GEPU in 2007-08 (Global Financial Crisis) and 2020 (COVID-19 Pandemic), as well as a general trend of increasing GEPU over time.

Additionally, we used both density plotting and summary statistics to examine the characteristics of the panel's variables. Firstly, focussing on the dependent and independent variables, FDI_s, GDPc, CEPU, and GEPU were significantly positively skewed, and might benefit from log-scaling in some model versions. Secondly, FDI_i and FDI_s were both highly leptokurtic, with both variables containing significant outlier observations. While log-scaling might help to reduce the effect of positive statistical outliers, in the robustness checks section of this paper we also apply winsorisation and trimming techniques to assess how sensitive our coefficient estimates are to statistical outliers.

Furthermore, we also produced Variance Inflation Factor (VIF) estimates. We tested four models. Firstly, a simple OLS regression, including all five instrumental variables as independent variables. Secondly, the first VIF model but with independent variables lagged by two years. Thirdly, a log-log equivalent of the first VIF model. Fourthly, a log-log equivalent of the second VIF model. These approaches were chosen as they represent the main range of specifications tested in the OLS section of this paper. All VIF estimates derived were under the critical values of five and ten, meaning that the VIF tests do not detect significant multicollinearity issues.

3.2 Research Question and Methodology

To assess the impact of CEPU and GEPU on FDI inflows across the 38 OECD member countries, we start with a simple panel Ordinary Least Squares (OLS) specification, for observation i at time t. Assuming that we are regressing the set of independent variables $\{x_1, x_2, ...\}$, we define the generalised OLS equation as:

$$y_{i,t} = \beta_0 + \beta_1 x_{1_{i,t}} + \beta_2 x_{2_{i,t}} + \cdots + \varepsilon_{i,t}$$

However, as outlined in the empirical section of the literature review, there is a potential 'lag effect' between independent variables (macroeconomic conditions) and the dependent variable (FDI inflows). We therefore modify our generalised OLS equation to the below, where $l = \{0, 1, 2\}$:

$$y_{i,t} = \beta_0 + \beta_1 x_{1_{i,t-l}} + \beta_2 x_{2_{i,t-l}} + \cdots + \varepsilon_{i,t}$$

We then test alternative Fixed Effects (FE) and Random Effects (RE) specifications. FE modelling controls for time-invariant differences between panel countries, whereas RE modelling allows for the inclusion of explanatory time-invariant variables. Furthermore, we also test Two-Way Least Squares (2SLS) specifications, to attempt to control for endogeneity issues in independent variables where necessary by first predicting their values using an instrumental variable.

3.3 Empirical Model

The primary goal of this modelling is to better understand the effect of CEPU and GEPU on country-level FDI inflows, and the relative importance of other macroeconomic factors on FDI inflows. Macroeconomic factors outside of EPU are captured through control variables (FDI_s, GDPg, and GDPc) and help to improve the robustness of CEPU and GEPU effect estimates. Where derived results for control variables are significant, they will also be discussed further.

The initial model will log-scale GDPc, due to both strong precedent for the approach as outlined in the literature review, and issues of positive skew identified during data testing. The dependent variable is $FDI\_i_{i,t}$, defined as FDI inflows into country *i* at time *t* as a percentage of GDP. Independent variables are denoted as var_{t-l} or $var_{i,t-l}$, depending on whether they were country-specific or global, and where *l* represents a lag of between 0 and 2 years $l = \{0, 1, 2\}$. Therefore, the baseline model specification is as follows:

$$FDI\_i_{i,t} = \beta_0 + \beta_1 FDI\_s_{i,t-l} + \beta_2 lnGDPc_{i,t-l} + \beta_3 GDPg_{i,t-l} + \beta_5 CEPU_{i,t-l} + \beta_4 GEPU_{t-l} + \varepsilon_{i,t}$$

As outlined in the previous subsection, we will then expand further on this initial modelling by comparing the best-performing lagged baseline model to its log-log equivalent. We then use FE and RE estimation to control for unobserved time-invariant effects, and 2SLS estimation to attempt to better account for endogeneity issues in independent variables where needed. As previously outlined, a variety of experimental instrumental variables will be tested to attempt to control for endogeneity, including measures of stock market volatility (VIX, SPV), gold prices (GLD), and exchange rate volatility (EMV, ERVX).

Finally, we conclude that there is insufficient evidence to suggest that the alternative estimation methods tested performed significantly better than their OLS specification equivalents. We also conduct robustness checks, namely model re-specification, and alternative treatment of statistical outliers, to assess the stability and robustness of the coefficient estimates. Figure 3 below provides a summary of the models examined in this dissertation, including a 'model code' for reference.

Figure 3: Model Specification Code Lists

Model Code	Equation
OLS1	$FDI\_i_{i,t} = \beta_0 + \beta_1 FDI\_s_{i,t} + \beta_2 lnGDPc_{i,t} + \beta_3 GDPg_{i,t} + \beta_5 CEPU_{i,t} + \beta_4 GEPU_t$
OLS2	$FDI\_i_{i,t} = \beta_0 + \beta_1 FDI\_s_{i,t-1} + \beta_2 lnGDPc_{i,t-1} + \beta_3 GDPg_{i,t-1} + \beta_5 CEPU_{i,t-1} + \beta_4 GEPU_{t-1}$
OLS3	$FDI\_i_{i,t} = \beta_0 + \beta_1 FDI\_s_{i,t-2} + \beta_2 lnGDPc_{i,t-2} + \beta_3 GDPg_{i,t-2} + \beta_5 CEPU_{i,t-2} + \beta_4 GEPU_{t-2}$
OLS4	$\ln(FDI\_i_{i,t}) = \beta_0 + \beta_1 \ln(FDI\_s_{i,t-2}) + \beta_2 \ln(GDPc_{i,t-2}) + \beta_3 \ln(GDPg_{i,t-2}) + \beta_5 \ln(CEPU_{i,t-2}) + \beta_4 \ln(GEPU_{t-2})$
FE1	OLS3, but modelled using Fixed Effects
RE1	OLS3, but modelled using Random Effects
FE2	OLS4, but modelled using Fixed Effects
RE2	OLS4, but modelled using Random Effects
2SLS1	OLS4, but $\ln(SPV_{i,t-2})$ is an Instrumental Variable for $\ln\left(FDI_{s_{i,t-2}}\right)$
2SLS2	OLS4, but $\ln(SPV_{i,t-2})$ is an Instrumental Variable for $\ln(GDPc_{i,t-2})$
2SLS3	OLS4, but $\ln(GLD_{i,t-2})$ is an Instrumental Variable for $\ln(GDPc_{i,t-2})$
2SLS4	OLS4, but $\ln(VIX_{i,t-2})$ is an Instrumental Variable for $\ln(GDPc_{i,t-2})$
OLS5	OLS4, but with 1% variable winsorisation
OLS6	OLS4, but with 2.5% variable trimming
OLS7	OLS4, but with 2.5% variable winsorisation
OLS8	OLS4, but with $\ln(CEPU_{i,t-2})$ removed
OLS9	OLS4, but with $\ln(GEPU_{t-2})$ removed

4. Results

4.1 Main Specification Estimates

As outlined in section 3.3, we start with a general model of the form:

$$FDI\_i_{i,t} = \beta_0 + \beta_1 FDI\_s_{i,t-l} + \beta_2 lnGDPc_{i,t-l} + \beta_3 GDPg_{i,t-l} + \beta_5 CEPU_{i,t-l} + \beta_4 GEPU_{t-l} + \varepsilon_{i,t}$$

As outlined in the literature review section, there is strong precedent for lagging independent macroeconomic variables to capture the delay between a firm deciding to invest in a country and that investment 'landing'. A two-year lag is common in FDI econometric literature. However, we will test a range of lag structures, to see which best suits the panel. Firstly, we will test *l = 0* years, the hypothesis being that there is no delay between deciding to invest abroad and the investment 'landing'. Secondly, we will test *l = 1* year, and finally *l = 2* years, the hypothesis being that there is some delay between deciding to invest in a country and the investment 'landing'.

As outlined previously, our GDP per capita data is positively skewed. As is common in both general and FDI-specific econometric literature, we log-scale GDPc for the baseline linear-linear OLS model.

Table 1: AIC/BIC testing and optimal lag length selection

Model Formula	AIC	BIC
OLS1, no lag on independent variables	2,037.45	2,060.30
OLS2, one-year lag on independent variables	2,009.15	2,031.72
OLS3, two-year lag on independent variables	1,946.62	1,968.90

We start by testing optimal lag length, where lower AIC/BIC values represent better model fit. Therefore, we can see that for both our AIC and BIC estimates, the model with a two-year lag is a better model fit than the model with a one-year lag, which in turn is a better model fit than the model with no lag. We therefore lag independent variables by two years, in line with previous econometric literature.

Table 2: Linear-Linear and Log-Log versions of the optimal lag model

Model	AIC	BIC	Log-Likelihood	R^2	Adj. R^2	RESET p-value
OLS3, Linear-linear, two-year lagged independent variables	1,946.62	1,968.90	(-) 967.31	0.235	0.223	0.000
OLS4, Log-log, two-year lagged independent variables	640.46	661.42	(-) 314.23	0.450	0.438	0.167

Next, we test the relative performance of linear-linear and log-log variations of the best-performing lagged model. For simplicity, we chose to log-scale GDPc and not lnGDPc for the log-log model, although future research could test both approaches. Across the AIC, BIC, Log-Likelihood, R^2, and Adjusted R^2 metrics, the log-log version of the model performs better than the linear-linear version.

Additionally, the p-value for the RESET test is less than 0.05 for the linear-linear model, meaning that we reject the null hypothesis (H_0), and the linear-linear model may suffer from non-linear omitted variables. However, the RESET test p-value for the log-log model is above 0.05, meaning that we do not reject H_0, and the model does not suffer from non-linear omitted variables. This suggests that the use of a log-log model with two-year lagged independent variables is preferred.

Next, we test both FE and RE for both the linear-linear and log-log model specifications. Starting with the linear-linear model, we reject H_0 for both the Breusch-Pagan ($p = 0.014$) and Hausman ($p = 0.000$) tests. Rejecting H_0 for the Breusch-Pagan test means that the country-specific error is not zero and effects are random, suggesting that RE is preferred to OLS. Rejecting H0 for the Hausman test means that the error term is correlated with at least one explanatory variable, suggesting that FE is preferred to RE. Hence, for the linear-linear model, FE is preferred to RE which is preferred to OLS.

For the log-log model, we do not reject H_0 for the Breusch-Pagan test ($p = 0.463$), but we reject H0 for the Hausman test ($p = 0.000$). Not rejecting H0 for the Breusch-Pagan test means the country-specific error is zero, effects are not random, and OLS is preferred to RE. Rejecting H_0 for the Hausman test means that the error term is correlated with at least one explanatory variable, suggesting that FE is preferred to RE. Hence, for the log-log model, FE is preferred to RE, and OLS is preferred to RE, but we cannot identify whether FE or OLS are preferred to one another.

From this point onwards in model development, analysis focusses on the log-log versions of model specifications, although for completeness we will still test for endogeneity issues in both specifications. Additionally, while only one predictor variable was statistically significant for the FE model, as compared to two for the RE model, we still recommend FE as the preferred modelling approach between the two. This is informed by the results of Breusch-Pagan and Hausman testing, but also the FE model performing better according to metrics such as Log-Likelihood and AIC/BIC.

However, when comparing the Fixed Effects log-log model to its OLS counterpart, there was marginal difference across key metrics such as AIC scores, Log-Likelihood scores, and overall variable significance. Therefore, both Fixed Effects and OLS are both arguably justifiable approaches for the log-log model. Given the evidence for choosing FE over OLS was not conclusive, we continue to use OLS as the main modelling approach.

Table 3: Granger Causality Test, Lagged Independent Variables

X	X does not Granger-cause FDI inflows (FDI_i)		FDI inflows (FDI_i) do not Granger-cause X	
	F-statistic	p-value	F-statistic	p-value
FDI_s	0.904	0.342	0.360	0.549
GDPc	5.188	0.023**	4.693	0.031**
GDPg	0.024	0.878	0.057	0.811
CEPU	0.023	0.879	5.607	0.018**
GEPU	6.554	0.011**	0.407	0.524
lnGDPc	0.023	0.881	1.196	0.275

Note: Independent variables are lagged by 2 periods. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively.

We next address the issue of potential endogeneity between variables. For the linear-linear model, there is a Granger-causal relationship between both GDPc and GEPU and the dependent variable. However, we also identified a Granger-causal relationship between the dependent variable, and GDPc and CEPU. This breaks assumptions of variable exogeneity for GDPc and CEPU for the linear-linear model.

Table 4: Granger Causality Test, Logged Variables, Lagged Independent Variables

X	X does not Granger-cause FDI inflows (lnFDI_i)		FDI inflows (lnFDI_i) do not Granger-cause X	
	F-statistic	p-value	F-statistic	p-value
lnFDI_s	63.380	0.000***	5.370	0.021**
lnGDPc	20.210	0.000***	11.541	0.001***
lnGDPg	0.080	0.777	13.817	0.000***
lnCEPU	0.005	0.945	1.014	0.315
lnGEPU	3.605	0.058*	0.193	0.660

Note: Independent variables are lagged by 2 periods. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively.

For the log-log model, there is a Granger-causal relationship between FDI_s, GDPc, and GEPU and the dependent variable. However, there is also a Granger-causal relationship between the dependent variable and FDI_s, GDPc, and GDPg. For FDI_s and GDPc this represents simultaneity, a two-way variable relationship. For GDPg this represents reverse causality, a wrong-way variable relationship (relative to initial assumptions).

Both issues break assumptions of variable exogeneity for the log-log model specifications. Therefore, we next implement instrumental variables in a Two-Stage Least Squares (2SLS) specification to attempt to address these endogeneity issues.

Table 5: Instrumental Variable Models and Specification Test Results

Variable	Statistical Test	lnSPV	lnERVX	lnEMV	lnGLD	lnVIX
lnFDI_s	Sargan	0.000	0.000	0.000	0.000	0.000
	Weak Instrument	8.382	0.648	0.001	0.035	0.193
	Hausman	0.488	0.136	0.785	0.106	0.409
lnGDPc	Sargan	0.000	0.000	0.000	0.000	0.000
	Weak Instrument	9.893	6.471	1.479	12.178	17.478
	Hausman	0.488	0.136	0.785	0.106	0.409
lnGDPg	Sargan	0.000	0.000	0.000	0.000	0.000
	Weak Instrument	2.804	5.311	0.004	1.092	0.072
	Hausman	0.488	0.136	0.785	0.106	0.409

Note: Independent variables are lagged by 2 periods. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively.

Table 5 above tests five proposed instrumental variables for each of the three independent variables identified as having endogeneity issues by the Granger causality test. From the results, we can see that two instruments were close to but did not pass the common threshold of ten on the weak instrument test: SPV as an instrument for FDI_s and SPV as an instrument for GDPc. Additionally, a further two instruments passed the common threshold of ten for the weak instrument test: GLD as an instrument for GDPc and VIX as an instrument for GDPc.

Interestingly, all models tested rejected H0 for the Sargan test and failed to reject H0 for the Hausman, suggesting that the overriding restrictions (instrumental variables) used are not valid. There is correlation between instrumental variables and error terms, due to either omitted variable bias or variable measurement error in one of the independent variables. Furthermore, failure to reject H_0 for the Hausman test implies that the independent variables are uncorrelated with model errors, and therefore that 2SLS does not perform significantly better than OLS for this panel.

This may seem to conflict with the findings of the Granger causality testing, which implied that endogeneity issues were present for the variables FDI_s, GDPc, and GDPg. However, these results are complementary: Granger causality testing indicated potential endogeneity issues, and Sargan and Hausman testing indicated that the 2SLS specifications do not perform significantly better than OLS for addressing those endogeneity issues. We interpret this to mean that while these instrumental variables may have potential (Weak Instrument test), there are potential misspecification issues with the model (Sargan and Hausman tests). Hence, while our 2SLS model outputs may still be of interest, we do not find sufficient evidence to change to 2SLS modelling as the preferred modelling approach.

Table 6: Two-Stage Least Squares Models, with Instrumental Variables

		2SLS1	2SLS2	2SLS3	2SLS4	OLS4
constant	coefficient	0.766	-4.495	9.720	-3.573	0.442
	p-value	0.645	0.608	0.328	0.546	0.787
lnFDI_s	coefficient	1.218	0.954	1.045	0.960	0.985
	p-value	0.004***	0.000***	0.000***	0.000***	0.000***
lnGDPc	coefficient	-0.068	0.596	1.132	0.484	-0.004
	p-value	0.747	0.576	0.338	0.489	0.980
lnGDPg	coefficient	-0.110	-0.009	-0.069	-0.012	-0.029
	p-value	0.597	0.916	0.455	0.877	0.729
lnGEPU	coefficient	-0.302	-0.351	0.011	-0.328	-0.225
	p-value	0.204	0.212	0.967	0.106	0.228
lnCEPU	coefficient	-0.407	-0.536	-0.149	-0.511	-0.402
	p-value	0.041**	0.073*	0.714	0.029**	0.013**
Sargan		0.000	0.000	0.000	0.000	
Weak Instrument		8.382	9.893	12.178	17.478	
Hausman		0.488	0.488	0.106	0.409	

Note: Independent variables are lagged by 2 periods. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively.

Starting with FDI_s, we can see that countries with a 1% higher existing FDI stock receive between 0.95% and 1.22% higher FDI inflows in a given year, reflecting the findings of previous papers such as Jardet et. al. (2023). This could be capturing unobserved effects, for instance the benefits of historical openness to FDI, or a more indirect effect, such as how attractive a country's business environment is. However, this could also be autocorrelative and simply capturing general increases in both FDI_s and FDI_i over time or between countries, or perhaps a combination of unobserved and autocorrelative effects. Both GDPc and GDPg had a statistically insignificant effect on FDI inflows in these models.

GEPU increasing by 1% was associated with between a (-)0.35% and +0.01% change in FDI inflows, with GEPU negatively impacting FDI in all models except 2SLS3. While GEPU coefficient significance is low, as discussed in section 4.3 this may be impacted by multicollinearity between CEPU and GEPU. CEPU increasing by 1% was associated with between a (-)0.54% and (-)0.15% change in FDI inflows, with moderate statistical significance for this coefficient across most models.

In summary, there is a negative and statistically significant relationship between CEPU and FDI_i for OECD member countries. Additionally, there is a negative but statistically insignificant relationship between GEPU and FDI_i. Both results broadly align with the empirical findings discussed in the literature review in terms of effect direction.

4.2 Diagnostic Tests

Panel data models are often susceptible to a unique set of issues, simply due to the nature of a panel data construction. Therefore, we test the performance of the preferred models across different modelling methods, using panel-specific tests where necessary. The models tested are all log-scaled and use lagged independent variables and include the best-performing OLS

(OLS4), Fixed Effects (FE2), Random Effects (RE2), and Two-Stage Least Squares (2SLS3, 2SLS4) models.

Table 7: Model Diagnostic Tests

	OLS4	FE2	RE2	2SLS3	2SLS4
Pesaran CD test for cross-sectional dependence in panel models	0.022**	0.155	0.033**	0.012**	0.002***
Breusch-Godfrey/Wooldridge test for serial correlation in panel models	0.000***	0.016**	0.000***	0.000***	0.000***
White's test for heteroscedasticity	0.328	0.488	0.309	0.493	0.344

Note: *, **, and *** represent significance levels of 10%, 5%, and 1% respectively.

One common issue with panel data is cross-sectional dependence, which refers to instances where error terms are correlated across different cross-sectional units (countries). As Table 7 above shows, we reject H_0 for four of the five models, meaning cross-sectional dependence is present for all preferred models except FE2. This could potentially bias coefficient estimates, and increase standard error size, which may be noteworthy when interpreting final model results.

Another common issue with panel data is serial correlation (autocorrelation). This refers to instances where the model's idiosyncratic error terms are correlated over time. We reject H_0 for all models, meaning that serial correlation is present in all five of the preferred models. However, as outlined previously, HAC-robust standard errors have been used in all models discussed in this paper, which should help to minimise the impact of serial correlation on coefficient estimates.

A final common issue with panel data is heteroscedasticity, where the error term's variance is not constant across observations. We do not reject H_0 for White's test for all models, suggesting there are no significant heteroscedasticity issues in the preferred models.

4.3 Robustness Checks

We next conduct robustness checks on empirical models. Firstly, Table 8 shows alternative treatment of statistical outliers, which is important as it examines how sensitive coefficient and p-value estimates are in the preferred final model (OLS4) to statistical outliers. We apply variable winsorisation at the 1% and 2.5% quantiles, and variable trimming at the 2.5% quantile, using two-tailed quantile thresholds.

Table 8: Alternative Treatment of Statistical Outliers

	Final (OLS4)		Winsorised (1%) (OLS5)		Trimmed (2.5%) (OLS6)		Winsorised (2.5%) (OLS7)	
	coeff.	p-value	coeff.	p-value	coeff.	p-value	coeff.	p-value
constant	0.442	0.787	0.570	0.727	0.238	0.898	0.781	0.632
lnFDI_s	0.985	0.000***	0.985	0.000***	0.983	0.000***	1.016	0.000***
lnGDPc	(-)0.004	0.980	(-)0.014	0.935	(-)0.090	0.644	(-)0.041	0.810
lnGDPg	(-)0.029	0.729	(-)0.030	0.725	0.044	0.628	(-)0.026	0.763
lnCEPU	(-)0.402	0.013**	(-)0.420	0.015**	(-)0.170	0.391	(-)0.417	0.019**
lnGEPU	(-)0.225	0.228	(-)0.213	0.262	(-)0.239	0.231	(-)0.224	0.239
Obs.	243		243		211		243	
Adj. R^2	0.438		0.437		0.333		0.434	

Note: Independent variables are lagged by 2 periods. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively.

Having a higher existing FDI stock (FDI_s) was positively associated with higher future FDI inflows (FDI_i). This could be capturing some measure of historical 'openness' to FDI, where foreign firms prefer to invest in nations that have been more open to inward FDI historically, or alternatively be capturing an autocorrelative relationship between FDI_s and FDI_i.

Coefficient estimates for both GDPc and GDPg were statistically insignificant, suggesting that neither a country's lagged GDP per capita nor its lagged GDP growth rate have a statistically significant impact on FDI inflows. Finding a statistically insignificant relationship between GDPc and FDI inflows is not entirely surprising, given existing literature demonstrated mixed findings for this variable. However, finding no statistically significant relationship between GDPg and FDI inflows is more interesting, and runs contrary to expectations based on empirical literature.

Furthermore, all four of the above models demonstrated a negative relationship, where higher levels of CEPU and GEPU led to lower FDI inflows. The above modelling suggests that a 1% increase in CEPU is associated with between a 0.17% and a 0.42% decrease in FDI inflows, or between a 0.40% and 0.42% decrease in FDI flows amongst only statistically significant estimates. Additionally, a 1% increase in GEPU is associated with between a 0.21% and a 0.24% decrease in FDI inflows, although these estimates were not statistically significant. These findings are therefore aligned with those seen earlier in this paper and in the literature review.

Additionally, it is interesting to note that CEPU is a more statistically significant predictor than GEPU across three of the four models above. Table 9 below shows the impact of changes in the independent variables included in each model on the magnitude, direction, and significance of EPU coefficient estimates. This is important because it allows us to examine whether CEPU and GEPU are capturing different effects or are multicollinear.

Table 9: Specification Changes using Economic Policy Uncertainty Variables

	CEPU and GEPU (OLS4)		CEPU Removed (OLS8)		GEPU Removed (OLS9)	
	coefficient	p-value	coefficient	p-value	coefficient	p-value
constant	0.442	0.787	1.905	0.036**	0.258	0.874
lnFDI_s	0.985	0.000***	1.034	0.000***	0.973	0.000***
lnGDPc	-0.004	0.980	-0.226	0.011**	-0.045	0.791
lnGDPg	-0.029	0.729	-0.002	0.969	-0.013	0.879
lnCEPU	-0.402	0.013**			-0.493	0.001***
lnGEPU	-0.225	0.228	-0.454	0.000***		

Note: *, **, and *** represent significance levels of 10%, 5%, and 1% respectively.

Starting first with the magnitude of coefficient estimates, the removal of one EPU variable causes an increase in the absolute magnitude of the other. Furthermore, the removal of CEPU makes GEPU statistically significant, and the removal of GEPU makes CEPU more statistically significant, suggesting that we may obtain more robust estimates of both variables when considering them in separate models. Hence, there are potential multicollinearity issues between CEPU and GEPU.

This may seem surprising, as both variables demonstrated relatively low VIF scores earlier in the paper, and weak to moderate correlation (R = 0.35). However, the theory behind this, that changes in GEPU can lead to changes in CEPU or vice-versa, is intuitive. Therefore, we use the phrase 'potential multicollinearity issues', as this effect potentially requires further study.

The results of the robustness checks for CEPU and GEPU in Table 9 are similar to the findings shown in Table 8. That is, amongst statistically significant coefficient estimates, a 1% increase in CEPU is associated with between a 0.40% and 0.49% decrease in FDI inflows, and a 1% increase in GEPU with a 0.45% decrease in FDI inflows. These findings align with earlier models, and literature review findings.

5. Limitations and Future Research

In this paper, we studied the relationship between EPU and FDI inflows. However, there are limitations and caveats to this work. While testing suggested that the use of a log-log functional form might be preferred to linear-linear, and may simplify coefficient interpretation, it also reduced the number of valid observations, as 8.8% of observations for FDI_i and 14.3% for GDPg were either negative or zero in the original dataset. This introduces a potential bias in coefficient estimates, which future research might wish to avoid by using inverse hyperbolic sine transformation rather than log-scaling, which can handle non-positive values (Norton, 2022).

Additionally, data coverage for the CEPU variable was incomplete, with CEPU data only present for 39.5% of observations in the original panel dataset, or fifteen of the 38 OECD member countries. This data limitation creates uncertainty in interpreting coefficient estimates, which could be biased toward nations where CEPU data was available. Therefore, future research might seek to increase CEPU data coverage, for instance using variable imputation, or an alternative measure of CEPU.

Moreover, we can see that while GEPU was statistically insignificant in Table 9, the removal of CEPU in model OLS8 caused GEPU to become statistically significant. This creates uncertainty in the interpretation of both variables, as if multicollinearity is present, this could potentially lead to inflated standard errors and p-values (Wooldridge, 2006, p. 144). One option to address this in future research could be Ridge regression, which is designed to produce stable coefficient estimates when a model contains multicollinearity issues in its predictor variables.

This paper also expanded on existing literature by identifying potential alternative instrumental variables to control for endogeneity issues. We identified potential instrumental variables for FDI_s (potentially instrumented by SPV) and GDPc (potentially instrumented by SPV, GLD, or VIX). Future research might test the performance of these novel instrumental variables against the more established 'exogenous election timings' instrument.

Finally, future research might attempt to reproduce this study with a different panel composition, to see if derived results are relatively similar or diverging for other economic development regions.

6. Conclusion

This paper examined the relationship between EPU and FDI inflows and tested alternative instrumental variables beyond those already explored in the literature. To the best of our knowledge, this research is the first to examine this relationship specifically for the 38 OECD member countries, and the first to examine the potential of a novel set of instrumental variables (VIX, SPV, GLD, ERVX, EMV) to account for endogeneity between country-level macroeconomic conditions and FDI inflows.

The theoretical background of the literature review generally suggested that greater uncertainty levels negatively impact investment. However, some theoretical literature suggested that under certain conditions, the inverse may be true. Existing empirical literature strongly suggested a negative relationship between greater levels of uncertainty and FDI inflows.

Estimates of the effect of CEPU on FDI inflows were statistically significant at the 5% level across all models except OLS6 (Tables 8 and 9). Coefficient estimates ranged from (-)0.49 to (-)0.17, and from (-)0.49 to (-)0.40 amongst only statistically significant estimates. This is broadly in line with estimates of from (-)0.69 to (-)0.25, and from (-)0.69 to (-)0.67 for statistically significant estimates, outlined in the literature review (for 116 countries at a range of stages of economic development).

Estimates of the effect of GEPU on FDI inflows ranged from (-)0.21 to (-)0.45, or simply (-)0.45 amongst statistically significant estimates. This finding broadly aligns with a statistically significant estimate of (-)0.39 outlined in the literature review (for nineteen high-income countries).

Our methodology was broadly aligned with these comparative studies in its use of log-log modelling and lagged independent variables. The main differences were the panel scope and the regression type (OLS vs. ARDL). While our GEPU estimate is similar in scale to empirical literature, our OECD-specific CEPU estimate was noticeably lower than the effect identified in empirical literature.

This suggests that FDI inflows into OECD countries are less sensitive to increasing CEPU relative to a panel of 116 countries at a range of stages of economic development. This reflects the narrative of Aizenman and Marion (1999) outlined in the literature review, that FDI inflows in developing economies are relatively more sensitive to changes in EPU than FDI inflows in developed economies.

Potential multicollinearity issues were identified between CEPU and GEPU. Future research could consider the use of alternative modelling approaches such as Ridge regression to better account for this.

The results of our Granger causality testing suggested that FDI stock, GDP per capita, and GEPU may be the factors which have the greatest impact on FDI inflows. While policymakers may not be able to influence GDP per capita and GEPU directly, the FDI stock variable may be capturing unobserved variance in factors such how attractive a country's business environment is, historical openness to FDI, and reputation as an FDI host country.

Regarding the control variables, we were not able to find a statistically significant relationship for GDPc and GDPg with FDI_i, after controlling for other factors. FDI_s was statistically significant across all models in section 4.3, ranging from 0.97 to 1.03. This might suggest that countries seen as more historically open to FDI are likely to receive greater FDI inflows in future. However, this finding might be capturing not only the intended effect, but also some unobserved variance from potentially omitted variables and autocorrelative effects. Additionally, Table 4 identified simultaneity issues between the log-scaled versions of FDI stock and FDI inflows, and as such we should be careful interpreting this coefficient.

There is an assortment of policy approaches by which countries could reduce uncertainty in their economic policymaking, but identifying specific policies is outside of the scope of this paper. However, the results discussed in this section may be useful to government officials in forecasting country-level FDI inflows. Additionally, they may be of interest to those attempting to quantify the expected impact of a change in policymaking or governance on EPU, and by extension on FDI inflows.

Future research might implement inverse hyperbolic sine variable transformations, to avoid data loss when handling negative values, and compare the best-performing novel instrumental variables with the instrumental variable currently most popular in existing literature, the 'exogenous election timing' dummy variable.

7. References

Abel, A. B., 1983. Optimal Investment Under Uncertainty. The American Economic Review, pp. 228-233.

Adkins, L. C., 2018. Using gretl for Principles of Econometrics, 5th Edition - Version 1.0. s.l.:Oklahoma State University.

Aitken, B. J. & Harrison, A. E., 1999. Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela. The American Economic Review, pp. 605-618.

Aizenman, J. & Marion, N., 1999. Volatility and Investment: Interpreting Evidence from Developing Countries. Economica, pp. 157-179.

Baker, S. R., Bloom, N. & Davis, S. J., 2016. Measuring Economic Policy Uncertainty. The Quarterly Journal of Economics, pp. pp. 1593-1636.

Bernanke, B. S., 1983. Irreversibility, Uncertainty, and Cyclical Investment. The Quarterly Journal of Economics, pp. 85-106.

Bloom, N., 2009. The Impact of Uncertainty Shocks. Econometrica, pp. 623-685.

Bruno, R. L., Campos, N. F. & Estrin, S., 2018. Taking stock of firm-level and country-level benefits from foreign direct investment. Multinational Business Review, pp. 1-73.

Choi, S., Furceri, D. & Yoon, C., 2020. Policy Uncertainty and Foreign Direct Investment. pp. pp. 1-47.

Department for International Trade, 2021. Understanding FDI and its impact in the United Kingdom for DIT's investment promotion activities and services: Phase 2 Analytical report. London: Department for International Trade.

Dixit, A. K. & Pindyck, R. S., 1994. Investment Under Uncertainty. Princeton: Princeton University Press.

Haque, M. A., Biqiong, Z., Arshad, M. U. & Yasmin, N., 2022. Role of uncertainty for FDI inflow: Panel econometric analysis of selected high-income nations. Cogent Economics & Finance.

Hartman, R., 1972. The Effects of Price and Cost Uncertainty on Investment. Journal of Economic Theory, pp. 258-266.

Hicks, J. R., 1939. Value and Capital. Oxford: Clarendon Press.

Jardet, C., Jude, C. & Chinn, M., 2023. Foreign Direct Investment under Uncertainty: Evidence from a Large Panel of Countries. Review of International Economics, pp. pp. 854-885.

Julio, B. & Yook, Y., 2016. Policy Uncertainty, Irreversibility, and Cross-Border Flows of Capital. Journal of International Economics, pp. pp. 13-26.

Keynes, J. M., 1936. The General Theory of Employment, Interest, and Money. s.l.:Macmillan.

Korley, M. & Giouvris, E., 2023. Does Economic Policy Uncertainty Explain Exchange Rate Movements in the Economic Community of West African States (ECOWAS): A Panel ARDL Approach. International Journal of Financial Studies, pp. no. 128, pp. 1-22.

Lipsey, R. E., 2002. Home and Host Country Effects of FDI. NBER Working Papers, pp. 1-76.

Luong, H. et al., 2017. How Do Foreign Institutional Investors Enhance Firm Innovation?. The Journal of Financial and Quantitative Analysis, pp. 1449-1490.

Nguyen, C. P. & Lee, G. S., 2021. Uncertainty, financial development, and FDI inflows: Global evidence. Economic Modelling.

Norton, E. C., 2022. The inverse hyperbolic sine transformation and retransformed marginal effects. The Stata Journal, pp. pp. 2-7.

Noviyanti, F., Sugema, I. & Irawan, T., 2023. Analysis of the Effect of Global Uncertainty and Financial Development on Foreign Direct Investment in Indonesia. Jurnal Ekonomi dan Kebijakan Pembangunan, pp. pp. 122-145.

OECD, 2022. The geography of foreign investment in OECD member countries: How investment promotion agencies support regional development, Paris: OECD Publishing.

OECD, 2025. Members and partners. [Online]

Available at: https://www.oecd.org/en/about/members-partners.html

Pindyck, R. S., 1982. Adjustment Costs, Uncertainty, and the Behavior of the Firm. The American Economic Review, pp. 415-427.

Smith, F., 2021. Uncertainty, Financial Development and FDI Inflows: France Evidence. Asian Business Research Journal, pp. pp. 7-13.

Tansuchat, R., Tarkhamtham, P., Puntoon, W. & Phadkantha, R., 2023. Forecasting Precious Metals Prices Volatility with the Global Economic Policy Uncertainty Index: The GARCH-MIDAS Technique for Different Frequency Data Sets. s.l., Springer, Cham, pp. 152-164.

Wooldridge, J. M., 2006. Introductory Econometrics: A Modern Approach. 3rd Edition. s.l.:Thomson South-Western.

World Bank Group, 2025. Series BX.KLT.DIlNV.WD.GD.ZS, Metadata Glossary. [Online]

Available at: https://databank.worldbank.org/metadataglossary/world-development-indicators/series/BX.KLT.DINV.WD.GD.ZS