How do Global Capital Flows Affect Economic Growth?

Unlocking the Puzzle via a Meta-Regression Analysis of Existing Studies

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Abstract

Due to the various empirical and theoretical perspectives of capital flows and management techniques' effects on economic growth, the thesis asks: "*How do Global Capital Flows Affect Economic Growth?*". The relationship between flow or flow-managing policies and measures and economic growth and development is well documented, with differing conclusions in Keynesian and neo-classical theory, as well as varying conclusions from more recent empirical assessments. The question is assessed through comparing the results from frequentist and Bayesian meta-regression analyses, an unusual approach in the social sciences, providing methodological innovation. The data of the thesis consists of extracted coefficients and between-study characteristics from existing and accessible empirical research from seventeen studies published in various journals from 1994-2022, compiled in an own set of metadata, who either investigate the relationship between capital flows and economic growth, capital controls on growth or various flow measures on economic growth. The empirical analysis of the data suggests a positive relationship between capital flows and economic growth, but there is slight publication bias present for positively reported results, and contextual and methodological moderators between studies highly impact the reported outcomes in research negatively. The findings highlight the need for specifically tailored and nuanced policy approaches and analyses, considering the economic conditions, data quality and potential biases when designing and implementing capital flow management strategies in domestic and foreign economies, to ensure effective economic policies that promote sustainable growth and mitigate potential financial risks and instability.

Acknowledgements

In an increasingly interconnected world, the movement of capital across borders has become a defining feature of the global economy. The dynamics of global capital flows have profound implications for economic growth, influencing everything from investment levels to exchange rates and financial stability. Understanding these flows and their impact is crucial for policymakers, economists, and businesses alike, and this thesis aims to increase the understanding of these dynamics. It is my hope that this thesis will contribute to a deeper understanding of global capital flows and inform future discussions and policies aimed at fostering sustainable economic growth worldwide.

The research presented here is the culmination of academic inquiry, extensive data analysis, and critical evaluation of existing literature. It builds upon a foundation of economic theory while incorporating contemporary developments, available data material and empirical studies to offer a nuanced perspective on a topic of paramount importance.

I wish to thank my supervisor of the master's thesis, Michael E. Alvarez, for his continuous guidance and efforts to help me improve my product until the very last in the process, always with quick responses and useful insights to my many e-mails and calls. Also, to my classmates for being such a great group of not just peers in comparative politics, but also the best of friends, providing unwavering support and encouragement throughout the last couple of years. Thank you to my family for providing the best care and support for me to follow my interests. Lastly, I want to thank scholars and institutions for previously conducted research on the topic, allowing me to build my metadata, and acknowledge that they are the ones who have made it possible for me to even start this project.

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Abbreviations

BP	Breusch-Pagan
CI	Confidence Interval
ESS	Effective Sample Size
ETI	Equal-Tailed Interval
FDI	Foreign Direct Investment
FE	Fixed Effects
GDP	Gross Domestic Product
HDI	Highest-Density Interval
HMC	Hamilton Monte Carlo
IMF	International Monetary Fund
IQR	Interquartile Range
LRT	Likelihood-Ratio Test
MCMC	Markov Chain Monte Carlo
ME	Mixed Effects
MLM	Multilevel Model
MR	Meta-Regression
MRA	Meta-Regression Analysis
OECD	Organization for Economic Co-operation and Development
PCC	Partial Correlation Coefficient
Q-Q	Quantile-Quantile
R&D	Research and (Technological) Development
RE	Random Effects
ROPE	Region of Practical Equivalence
SMD	Standard Mean Deviate
SND	Standard Normal Deviate
TS	Time-Series
TSCS	Time-Series Cross-Sectional
WLS	Weighted Least Squares

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1 Introduction

When Robert Solow (1978, 39) asked: “Why does a public discussion of economic policy so often show the abysmal ignorance of the participants?”, he raised an important aspect of economic policy, where the policymakers, meaning governments, central banks and other financial institutions, so often refuse to account for and neglect the important shifts in the economy induced by their implemented policies, causing long-term effects on amongst other things, economic growth and development. This thesis will investigate some of these questions regarding the impact of economic policy, through a meta-regression analysis of literature on capital flows and capital flow management and their effects on economic growth.

1.1 Subject of Investigation – Liberal Capital Flow with Related Management Policies (Capital Controls) and Economic Growth

In the history of financial and economic policy, there have generally been two main types of perspectives related to capital flow and capital mobility; the first perspective sees international capital flows as an engine of growth and economic development, while the second perspective sees capital flows as a mechanism that induces instability in economies. These perspectives are definitely competing, as the first perspective encourages policies that increase flow to increase growth, while the second perspective encourages policies that limit international capital flows and insulate economies to protect them from crashing into financial ruin (B. J. Eichengreen 2004, 13).

In principle, the cycles of internal capital mobility are closely related to the cycles in foreign lending (Taylor 1996, 2). The liberalization of capital flows (also known as capital openness or/and the removal of capital controls) could be described as a counterreaction to the Bretton Woods system and the Keynesian ideology that ruled the economic world after the Second World War. Whereas the Bretton Woods system utilized fixed exchange rates and capital controls to protect countries from external shocks, the “Washington Consensus” broke down this movement through the 70s and 80s by removing government controls in order to allow markets to operate freely. One of the more visible liberal policy measures that was utilized by the developing countries as was the decontrol of foreign direct investment (FDI) (Joyce and Noy 2008, 413). Some countries liberalized capital flows through programs of the International Monetary Fund (IMF), while others decontrolled their flows independently (Joyce and Noy

2008, 414). Investigations of countries included in the IMF annual report shows that capital account openness has increased in all groups of countries from the early 1980s until the mid-2000s, where the early 1990s was the period with the most rapid increase in openness in the lower income countries (Jayadev 2007, 426).

Eichengreen (2004, 4) divides the 20th century into four distinct capital market regimes regarding capital flows. Net flows in the world have never been higher than up until 1914 before the first world war broke out, with free capital movements internationally. The second period after the world war saw a time of decreasing capital flows with tighter capital controls, where governments were more involved in sustaining flows. When the world reached the financial crisis and the following great depression of the 1930s, stronger and more active capital controls and policies were implemented in attempts to halt economic decline and increase stability. Strong capital controls were held up until the 1970s, when measures limiting transactions were lifted, introducing a new period of growing capital flows.

1.2 Existing Empirical Findings

Research suggests that capital controls if not implemented correctly and at the right time might reduce economic growth. In turn, weak or negative economic growth might lead to significant bank losses due to increased nonperforming loans. While being designed to stabilize financial systems, capital controls combined with global vulnerabilities such as high leverage and liquidity shortages could exponentially increase the impact of these underlying issues and thus in a worst case scenario cause a financial crisis (Zehri, Iben Ammar, and Ajili Ben Youssef 2023, 2). In the 90s, the debate on capital controls at the practical policy level consisted of when and how fast capital controls should be eliminated, and not so much if they should be eliminated (Edwards 1999, 66).

There has been a shift in this debate, especially after the international financial crisis in 2008, and capital controls are now part of financial policy as much as anything else in most economies. Research on capital controls on their impact on economic growth and financial stability is therefore essential for policymakers so that they do not implement policies that cause negative impacts. Much of this contemporary research shines light over both the beneficial and adverse effects of capital controls and other flow management techniques; while they can decrease the likelihood of banking crisis and thus stabilize the financial systems they are implemented in; they can also decrease economic growth (Zehri, Iben Ammar, and Ajili Ben Youssef 2023, 4). Their effects are therefore quite paradoxical, as they can increase the risk of what they’re trying to prevent by inducing stabilizing measures through policy. The scholarly work that encompasses the positive effects of capital controls highlights that the measures foster financial system stability, while some other research fail to establish an empirical link between capital controls and preventing banking crisis. The literature is however fairly in consensus that capital controls (regarding inflows) alone cannot eradicate financial stability (Zehri, Iben Ammar, and Ajili Ben Youssef 2023, 4). Some research goes further in extent to differentiate the effects of capital controls on inflows versus outflows, such as in Edwards (1999). In the case of Chile, which due to experiencing a traumatic currency crisis in the early 80s reformed the banking structure and set capital controls as tax on inflows to the country, there's no clear evidence to determine that the capital controls had any positive effects on financial stability, even though it achieved a more stable economy during the 90s (Edwards 1999, 78). In Ben Zeev (2017, 64), empirical evidence indicates that strict capital inflow controls "… moderate the effects of global credit shocks, lends credence to the potential viability of inflow controls as a stabilizing policy tool.". In other words, a contradictory statement to Edwards, as the claims are further elaborated to inference that inflow controls are effective measures to increase macroeconomic stability.

The contrary strategy to capital controls, capital account openness has also been assessed regarding banking crises. Research on this does not find any clear, obvious or significant relationship between capital accounts and banking crises, but some research indicates that there might be short-term fluctuations in trade, productivity or vulnerability due to the implementation of flow management policies by financial institutions (Zehri, Iben Ammar, and Ajili Ben Youssef 2023, 5).

1.3 Research Background for This Study: Survey of Previous Findings

In the literature of economy and political science, a large number of studies are determined to explain the relationship between the removal of capital controls, or in other words, the large liberalization of global financial policy and economic growth. A simple search in Google Scholar using the terms "capital control" and "economic growth" provides nearly five million search results, and as I later show, using only a control sample of four of the first articles from the first page of this search engine, they all provide different conclusions on the relationship between the two variables. Due to this variation in expected outcome, it is essential to run a meta-regression on the topic to further investigate and explain why the outcome varies across different studies. As per my knowledge, no qualitative or quantitative meta-analyses on capital controls or capital flows and economic growth have been published in any of the top journals neither in the field of economy or in the field of political science or political economy.

There have been conducted numerous studies on the liberalization of capital flows and economic growth. Some studies, such as Shen et al. (2010) examining international capital flows and economic growth, find that only increased FDI will result in an increase in economic growth for a panel data set of 80 countries from 1976-2007 with variation in income-levels, corruption, banking liberalization, crisis and human capital, whilst increased FPI in general causes unfavorable and negative effects on economic growth.

A study in Senegal in the period of 1970-2014 by Adams et al. (2017), find that there is no cointegration between aid or FDI and economic growth. They find on the other hand that remittances cause economic growth, whilst higher external debts have a negative impact on growth. This study then contradicts the inferences made of FDI and growth in Shen et al. (2010).

In Grilli & Milesi-Ferretti (1995), they use panel data of 61 countries to determine the effects of capital controls in different economies. While they find the determinants that likely cause stronger capital controls, such as large governments and lower-income countries, they find no robust correlations between controls and economic growth. They do, however, find that higher degrees of control are associated with higher inflation and lower real interest rates.
Another study, which is different from the other studies by including regime types when estimating the effects and relationship between capital controls and economic growth is Satyanath (2007). In this study, he finds that higher degrees of capital control negatively impact economic growth in authoritarian countries, while economic growth in democratic countries is insignificantly unaffected by capital controls.

The findings above, which are only very few examples of studies within the topic, imply that designing a meta-regression analysis to understand the actual impacts and effects of capital flows and capital flow regulations through capital controls on economic growth are crucial to understand the relationship and detrimental to enlighten policymakers in the decision-making process of implementing financial regulatory policy. Empirical researchers are inconclusive regarding the effects and relationship of both capital flow and management policies on economic growth, making meta-analysis a just research design to further investigate the relationship and help obtaining consensus.

1.4 The Aim of this Meta-Regression Analysis

The approach of this thesis to answer the main research question could be considered as a *descriptive*, *explorative,* and *explanatory* meta-regression analysis. The explorative aspect comes from that the thesis combines different methods of meta-regression seldomly used in the social sciences, but rather drawn from methodological designs in medicine and biology to further explore methodological differences also within the approaches of meta-analysis in political science, by investigating if different approaches will conclude with different outcomes, or in other words, if different approaches to meta-regression analysis make the same inferences of the data, and if so, how valid they are. One of the key aspects of meta-analysis of quantitative studies is to increase certainty in cause and effect conclusions within a particular research area, which makes it stand out from qualitative approaches to meta-analysis and meta-synthesis, who is more focused on seeking understanding and explaining phenomena (Walsh and Downe 2005, 204). This does not mean that we cannot seek understanding and explain things through quantitative meta-analysis, but that it is more fit to explain causes and effects within a phenomenon than the phenomenon themselves. The descriptive aspect comes from the thesis' aim to describe the existing research population, or data, by focusing on how the empirical findings vary due to the choices made by the researchers regarding methods and research design. The third and final aspect, the explanatory, comes from the thesis' aim to explain the differences in reported outcomes and effects of the study units in the metadata on capital flows and economic growth, based on between-study characteristics and how they affect the reported outcome, to determine the actual relationship between capital flows and economic growth[1].

1.5 Presenting the Main Research Question

Based on the existing empirical findings and research on capital flows and economic growth, providing nuanced and varying inferences on the effects, the following main research question is presented, as in the title:

"How do Global Capital Flows Affect Economic Growth?"

The main research question is assessed through three split research questions in the thesis by the use of meta-regression analysis (MRA). To better understand the overall impact of capital flows and their management on economic growth, the first question asks:

1) *What is the mean observed effect of capital flow and capital flow management techniques on economic growth?*

[1] There are essentially two important factors that are the focus of this thesis that fit into the realm of comparative politics and political research. First, the thesis seeks to explain the substantive issues related to how global capital flows affect economic growth in the complex and dynamic global economy. The second factor is the inclusion of innovative research methodology, which to my knowledge is not used in any form of political research, by combining and comparing the results of MRA in frequentist fixed and mixed effects models and Bayesian random effects models to validate the inferences drawn from real and hypothetical sample populations.

By synthesizing the findings from various empirical studies, the thesis seeks to determine the average effect size through meta-regression analysis, allowing for a quantitative assessment of the relationship. This question is important, because it is crucial for policymakers and researchers to have insights into both the magnitude and direction of the relationship between capital flows and economic growth. To assess the question of publication bias towards significant or positive results, the second question asks:

2) *Is there publication bias present in the published literature regarding the relationship?*

By identifying if journals preferentially publish studies with statistically significant or positive results, thus overlooking studies with insignificant or negative results, we also assess the validity of the meta-regression analysis. By examining the presence of publication bias, the study can assess the robustness of the conclusions drawn from the literature and mitigate the potential impact of selective reporting on the overall findings. This question underscores the importance of methodological rigor and transparency in synthesizing empirical research. The third additional questions is asking:

3) *What are the drivers or between-study characteristics that may or may not cause differences in the reported outcomes betwe*en *the relationship of capital flow and capital flow management techniques on economic growth in literature?*

This question explores the heterogeneity in reported outcomes across all study units, and thus seeks to identify some of the moderators or characteristics that contribute to variations in the observed effects. By identifying the characteristics that contribute to variations in the observed effects, the thesis provides nuanced insights into the dynamics in research underlying the relationship between capital flows and economic growth. It also highlights the need to account for heterogeneity and contextual factors in all empirical research, as when synthesizing empirical research in comparative politics and economics.

1.6 Scope of the Thesis

Capital flows and economic growth is a complex and dynamical relationship in an increasingly interconnected economic and financial world that moving capital across borders is a defining feature of, fostering the need for meta-analysis on the topic. My innovative contribution is that to my knowledge, this is the first meta-analysis on the topic, at least in a quantitative direction through meta-regression analysis. Due to the profound implications global capital flows have on economic growth, it is essential to provide a better understanding of the relationship. Innovation-wise and to my knowledge, it is also one of the first, if not the first of studies in political research and comparative politics combining and comparing frequentist and Bayesian MRA as the main research methodology, allowing for a deeper understanding of the dynamics on both a given and a hypothetically larger population.

The importance of doing meta-regression analysis on capital flow or managements effects on economic growth for comparative politics is also, as later shown, that capital flows are restricted through politically induced policies, and even though they at heart are economically measured variables, the political aspects of regulating and managing capital flows are just as important in real life politics as economics. The comparative aspect exists because studies on these relationships happen all over the world and on different periods of time, indicating that when a meta-regression analysis is conducted on empirical studies on the topic, you could argue that you also consider how these mechanisms vary across different political contexts. It also helps policymakers and scholars in understanding the factors of research that affect flow dynamics and economic growth, and also in the interplay between economic policies, political institutions and economic outcomes. Likewise, an important aspect of the thesis lies in the previously mentioned explorative, and to some degrees experimental research design when it comes to meta-regression analysis in political science, by testing and utilizing combinations of models more commonly used in other research disciplines, and thus being innovative in regards of methods in social science research.

1.7 Outline of the Thesis

The remainder of the thesis after this brief introduction is structured into six coming chapters. First, a chapter on theory that conceptualizes the terms for capital flow and related management policies and flow measures as independent variables of the meta-regression analysis, and then economic growth as the dependent variable of the studies in the metadata. The section also explains and operationalizes how these concepts are measured across research, and how it relates to this thesis. Further on, the chapter also presents competing theories and empirical evidence on how these concepts are related, and why the phenomenon is fit for further research. The next chapter presents the research design and methodology chosen as the preferred analytical tool for this meta-analysis, namely meta-regression analysis, more precisely, comparing models of frequentist and Bayesian meta-regression analysis as an innovative basis for political research, as well as the calculation of partial correlation coefficients to create comparable estimates across all the study units of the data. The chapter is divided into different sections that present meta-regression in general, before diving deeper into the two different models along with step-by-step instructions on how these models have been constructed (fit) and evaluated. Further on, it is shown how these models have been used to generate estimates of publication bias and how heterogeneity in the data is modelled.

The fourth chapter describes the data of the meta-analysis. First is a section presenting the selection criteria that were used to find and evaluate possible data units, then how the coefficients from the study units were extracted through a best-set extraction process of reported effects. The dataset with all the main estimates for the meta-regression is presented in this section, along with descriptive statistics of the variables in the dataset fit to the models as between-study characteristics of the study units.

The fifth chapter of the thesis presents all the results from the frequentist and Bayesian meta-regression models in order. At the very beginning of the chapter, descriptive statistics of the units are presented as trend-investigating measures of the reported effects, along with visual and statistical evaluations of possible publication bias regarding flows and growth. In total four regression models are presented in order, first a frequentist fixed effects model without moderators and a frequentist mixed effects model with moderators, along with model evaluations of the frequentist models. Second, the two Bayesian random effects models are presented, one without and one with moderator variables, along with model evaluations of the Bayesian models.

The sixth chapter of the thesis focuses on discussing all the relevant findings and key summaries against the research questions, and assesses the theoretical, practical and empirical implications induced by the results of the analysis, as well as potential limitations of the study.

The seventh and final chapter summarizes the thesis through concluding remarks and also provides guidance for further research and policymaking on capital flows.

2 Theory

2.1 Conceptualizations and Measurements

In order to understand the concepts and measurements of the study units in the meta-regression analysis of the thesis, this chapter will focus on conceptualizing the terms and operationalizing the measurements of capital flow, and its related management techniques induced by economic policy as the independent variables of those study units, as well as conceptualizing terms and operationalizing measurements of economic growth, the dependent variable of all study units in the meta-analysis. Understanding these concepts is crucial to understand why the implementation of economic policies by policymakers matters to growth and development, and why researchers care about them, and policymakers should.

The chapter also presents an overview of some of the influencing mechanisms between capital flows and economic growth, and why we expect, or not, capital flows to be a determinant of growth in modern and growing economies. An important notion regarding this thesis, is that while theory plays a part in interpreting and understanding the impacts of economic policy, its main mission is to explain and determine the existing empirical evidence regarding capital flows and economic growth. Theory is therefore used to understand the concepts in the data, while the innovation lies in the utilization of uncommon research methodology within political science research. Generally, theory is often undermined or underplayed in typical meta-analysis, as it is a methodological framework used to investigate empirical relationships. However, I still wish to devote time to theory in order to present the correct linkage between the terms and underlying mechanisms between capital flows and economic growth, so that the totality of the relationship is better understood, both empirically and theoretically, ensuring more valid inferences and rightful assessments of the implications later.

2.1.1 Conceptualization: Defining Capital Flow, Capital Flow Management Techniques and Economic Growth

Capital Flows and Capital Flow Management

Capital flows are one of the key factors that plays a big role in the global economy, and can be good indicators of the economic and financial well-being and conditions of countries and what plausible policy issues they have (Koepke 2019, 516). Generally, economists differentiate capital flows by two main categories, *net* capital flows and *gross* capital flows. Net capital flows refer to the current account (inflow) balance of the national economy, and gross capital flows refer to the domestic outward investment and foreign inward investment separately (outflow), capturing a two-way flow that also reflects changes in the assets and liabilities in the financial account (Koepke 2019, 520). Another way of understanding the difference between the two terms is to view net capital flows as an exchange of assets in return for goods and services, while gross capital flows are a trade of assets in return for other assets (Koepke 2019, 520–21).

To manage or regulate global and domestic capital flows, central banks and other financial institutions introduce what economists refer to as *capital controls*. Capital controls are a range of policies that can take many forms based on the needs of the individual economies. For instance, restrictions can be placed on foreign investment in certain sectors, on capital outflows, or on access to the domestic or foreign currencies (Siddiqui 2017, 565). Restrictions on flows are therefore directly related to capital accounts, which is also referred to as capital accounts openness, capital account mobility, capital-account liberalization and several other terms in economic and political research (Jeanne 2012, 203; Henry 2003, 91).

Capital controls are one of many capital flow management techniques implemented by financial systems crucial for overall stability by mitigating systemic risks and protecting individual financial institutions. In practice and theory, capital controls are "… rules, taxes or fees associated with financial transactions that discriminate between domestic residents and those outside the country" (Klein 2012, 5). These controls are further differentiated with administrative or market-based measures, where the first includes prohibitions on foreign borrowing or lending, whilst the latter includes cross-border taxes and banking requirements (Klein 2012, 5). An important notion is that legal controls that affect capital flow management or capital mobility do not always imply actual restrictions on these capital movements. In many of the modern economies, a salient trend in the private sector is finding ways to create loopholes around domestic legislation, by for instance simple mechanisms such as over-invoicing imports and under-invoicing exports. This again causes implications when scholars are to measure the true degree of financial integration, as the legal degree and actual degree of capital mobility might differ a lot (Edwards 1999, 67).

Capital controls can also be differentiated by whether they affect outflows or inflows, previously described as gross capital flows and net capital flows, respectively, and also what types of assets the controls are implemented on.

Schindler (2009) distinguishes between six categories of *assets*, that consists of "Money Market", "Bonds", "Financial Credits", "Equities", "Collective Investments", and "Direct Investment" (Klein 2012, 13–15). While the money market refers to securities with an original maturity of less than a year, bonds refer to bonds and other securities with an original maturity of more than a year. Financial credits include credits other than commercial credits. Equities include transactions involving shares and other securities not acquired for the purpose of long-term economic interest. Collective investments are share certificates and registry entries, such as mutual funds or unit and investment trusts. Direct investments are investments domestically and non-domestically for the purpose of establishing lasting economic relationships (Klein 2012, 15). Other researchers, such as Fernández (2016) have later extended the data by Schindler (2009) to include four additional asset categories. Controls on capital outflows are meant to deal with financial and currency issues domestically. One of two main types of outflow controls is what is known as “preventive controls”. These controls tighten in a situation when there is a severe balance of payments deficit domestically, but yet not devaluation crisis, and include for instance taxes on funds remitted abroad, dual exchange rates and prohibition of funds’ transfers (Edwards 1999, 68). The other type of outflow controls applies to countries that already face a major crisis and is known as “curative controls” due to the temporary tightening of controls on outflows, such as Malaysia in 1989-99. These controls include lowering interest rates and implementing pro-growth policies to add additional time into restructuring the financial sector (Edwards 1999, 70).

Capital accounts and related terms refers exclusively to the inflow of capital and resources to countries, and has been deemed to reduce costs of capital, increase domestic investments and raise the economic output of liberalizing economies (Henry 2003, 91). The capital controls received more support following the East Asian crisis in 1997–1998, since previous policies of capital liberalization because of International Monetary Fund (IMF) pressures resulted in a huge inflow of foreign capital into the East Asian economies, which was reflected in a lending boom and domestic banks taking greater risks. The governments then failed to prevent funds from being used to finance speculative activities (Siddiqui 2017, 565). The global financial crisis of 2008 also sparked a wave of support for capital controls, for instance in Brazil, which introduced taxes on all capital inflows except foreign direct investment (FDI) in 2009 (Jeanne 2012, 203). Capital controls have not gained exclusive support in literature, and some research suggests that the effectiveness of capital control policies for financial and macroeconomic stability is halted by leakages in the implementation process. Anyways, several central banks respond to surges in capital inflows by active policies induced to reduce vulnerability in the financial markets due to sudden reversals in capital inflows and outflows (Bengui and Bianchi 2014, 3).

The *liberalization of domestic stock markets* and allowing for foreign portfolio investments is one example of “liberal” capital controls, allowing for a higher amount of net capital flow (inflow) to the economy (Bae, Bailey, and Mao 2006, 405). *Financial Liberalization* can mean a number of different things based on how the term is conceptualized. A common way to conceptualize the term is to deem it as equity market liberalization, meaning to give foreign investors rights and opportunities to invest in domestic equity securities and domestic investors rights and opportunities to transact in foreign equity securities (Bekaert, Harvey, and Lundblad 2005, 3). These investment opportunities in equity-stakes are regulated through policies of capital control, where loose regulations cause the opportunity for higher inflows and outflows by increasing the availability of foreign capital into domestic economies and promoting financial development, and vice versa(Bekaert, Harvey, and Lundblad 2005, 3).

Foreign Direct Investments (FDI) are long-term global investments *between* economies, meaning that it has implications on inflow of capital to countries receiving FDI, and outflow of the countries investing into foreign economies (Azman-Saini, Baharumshah, and Law 2010, 1079). It is also known as transfers in the global economy, being critical to the formation of capital in both developing and developed countries (Iamsiraroj 2016, 116). FDI-policies are forms of regulations through capital controls, which we have directly linked to capital flow, often deemed to provide benefits (growth) when FDI-stimulating policies are implemented in FDI-recipient countries, and FDI flows could be therefore be a measure of openness and economic freedom on its own (Azman-Saini, Baharumshah, and Law 2010, 1080).

Economic Growth

When we talk about economic growth, we essentially describe one of three different concepts, either world growth, country growth or dispersion in income levels (Klenow and Rodríguez-Clare 1997, 597). The economic growth measured in the meta-analysis of this thesis is all related to country growth, so the question is then, what is country growth? While world growth tries to explain the continuous growth in income per capita in the world economy, country growth aggregates the same related concepts down to a country-level measure, often based on the Gross Domestic Product (GDP) of an economy (Klenow and Rodríguez-Clare 1997, 597–98). A country's economic growth may be defined as:

> "… a long-term rise in capacity to supply increasingly diverse economic goods to its population, this growing capacity based on advancing technology and the institutional and ideological adjustments that it demands." (Kuznets 1973, 247).

By this definition, there are three components to the economic growth of a country that all matter to the conceptualization, the country or state's ability to supply goods and services to its inhabitants, the advancement of technology and capable institutions that can meet the demands given by the capacity to supply, and advancements in technology. The underlying cause of the rise in demands for goods and services is then the economic growth in the country's population and its ability to afford more goods and services than previously. An easy-to-interpret explanation of economic growth is think of it as an "… improvement in economic welfare or as expansion in productive capabilities" (Nutter 1957, 51). This interpretation of growth states that **a)** everyone can afford more goods and services, and **b)** everyone can produce more goods and services. The interpretation does not declare that it is only applicable for the man on the street, or only applicable for the state per say, we must therefore assume that it is applies to all economic populations. Other definitions of economic growth are based on the rate of growth of capital and income, also known as the growth rate, which describes how much the production of goods and services has increased or decreased (Kaldor 1957, 594).

Different growth models in the theoretical literature have been developed, some important ones being the *neoclassical* (Solow 1956) and *endogenous* growth models. The neoclassical model by Solow sees long-run growth only as a result of technological progress or labor force growth, or a combination of both where technological progression results in labor force growth (Iamsiraroj 2016, 117). On the other hand, an endogenous model of growth introduces capital to its model as human capital accumulation and Research and Development (R&D) (Iamsiraroj 2016, 117).

2.1.2 Measurements: Operationalizing Capital Flow and Economic Growth

Measuring Capital Flows and Management

The removal and implementation of capital controls, liberalization or restricting of capital flow and degrees of capital openness more or less relate to the same concept as has been conceptualized above and ensures that alle the related terms can be used as independent variables for articles investigating economic growth as study units of the meta-analysis. The main source for capital openness has for a long time been the IMF *Exchange Arrangements and Exchange Restrictions*. Assessing the degree and intensity of restrictions to the mobility of capital has been an issue for many researchers in many studies, since many countries, even those relatively developed have maintained various forms of capital controls with various intensities that impacts the variables of interest differently. One of the ways of going around this issue is Quinn's Index, where the intensity of control on balance of payments is coded on data of statutory restrictions (Jayadev 2007, 426).

Another developed method of measuring capital openness is developed by Jayadev (2007), which is a slightly modified reproduction of the methodology of Quinn’s Index, and that has data for all countries in the IMF annual report, as Quinn’s Index originally only has data for four non-OECD countries for four years. At the same time, one wants to include studies in a meta-regression that utilize different conceptualizations and measurements of capital flow and capital control policies, as statistical methods can correct for the way different studies measure capital controls, and thereby overcome this issue. The most important aspect is however that the studies that are included in the metadata measure the same concept, even if they measure it using different methodologies or statistical calculations, as this could be one of the reasons for why studies on the topic conclude in different ways. By default, we are also interested in investigating if different conceptualizations of the independent variable result in differences in the reported outcomes on economic growth as the dependent variable.

As an example of what some of the metrics used to measure financial development is, Valickova, Havranek and Horvath (2015) provide four key metrics:

1. **Financial Depth**: It measures the size of the financial sector, often represented by the ratio of liquid liabilities to GDP, with variations such as M2 or M3.
2. **Bank Ratio**: Introduced by King and Levine, it emphasizes the importance of commercial banks in resource allocation but faces challenges in excluding non-bank financial institutions.
3. **Financial Activity**: Various measures include the ratio of private domestic credit to GDP or private credit to the private sector, offering insights into the size and quality of services provided by the financial system.
4. **Stock Market Development**: Expanding beyond banks, measures include market capitalization ratio, stock market activity, and turnover ratio.

Given that the financial and economic landscape is so wide, terms and concepts often interact with each other, and still affect the same outcome as proven in the conceptualization of the independent variables to the study units, meta-analysis is crucial to understand how conceptualizations and measurements of independent variables affect the reported effects on economic growth across the study units.

Measuring Economic Growth

One of the advantages that lie in the nature of measuring economic growth as a concept, is that the “components” of all economies are mostly the same, and that economies and related economic processes thus are comparable across regions, countries, states and continents (Kenny and Williams 2001, 3). In statistical research, this has resulted in a near general consensus on how economic growth is measured most commonly in relation to GDP-estimates.

For the study units included in the metadata, there are slight variations in how economic growth is measured. For instance, in Baharumshah and Thanoon (2006) they only use yearly values of GDP for countries as a measure for long-run country growth, while Sakyi et al. (2015) and Huang and You (2019) use the "real per capita income" or "real GDP per capita" of countries, meaning $\frac{GDP}{Capita}$ to control for population levels and thus get more comparable measures across countries. Completely different than any of the other studies, Eris and Ulasan (2013) measure growth with a set of variables based on the neoclassical growth theory, so the dependent variable of economic growth is more similar to an index than a single measure.

These four examples from the studies of the metadata prove the point that measuring the same concept can be done in many different ways of operationalization, further strengthening the need for meta-analysis to investigate what drives the reported outcomes on dependent variables in political research.

Figure 1 provides a graphical visualization of how the independent and dependent concepts are conceptualized and relevant.

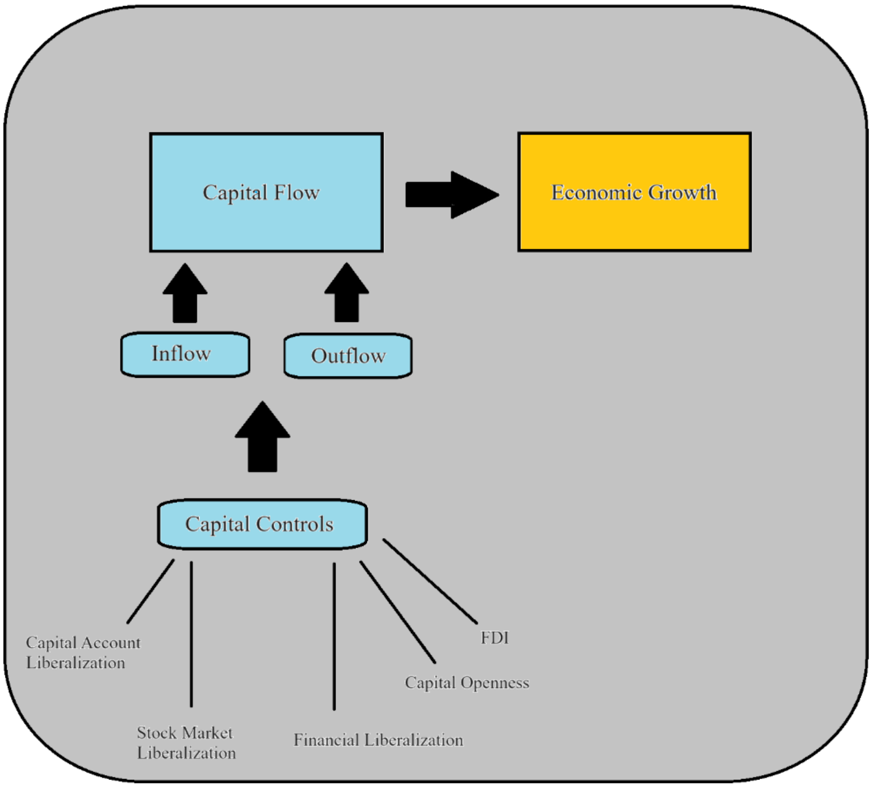


***Figure 1** Conceptualization of the Independent and Dependent Variables*

As figure 1 shows, capital account liberalization, stock market liberalization, financial liberalization, capital openness and FDI are all measures of, or restrictions and liberalizing measures of capital controls, which are the direct regulating mechanisms of capital flows. For instance, capital accounts are direct measures of net capital flows, while FDI can be a measure of both gross and net capital flows. By using these conceptualization of the independent variables, we ensure that capital flows always are the common factor affected as an independent variable measure.

2.2 Theory: How does Economic Openness Matter for Economic Growth?

In this section, general theories of mechanisms on how policies that regulate economic openness and capital flow affect economic growth are presented, to further strengthen the argument on why meta-analysis on the research topic is needed.

2.2.1 Why Capital Flows Could – and should – affect Economic Growth

Capital flows are, as explained, managed and regulated through a number of financial and economic policies named capital controls that are either liberating or restricting capital inflow and outflow to and from domestic economies by the responsible policymakers in a given economy. Thus, capital flow management is not just about questions of economy and finance, it is just as much about questions of policy and regulations.

In the process of economic growth and development, all political, social and demographic elements are paramount, as growth is not just about the aggregate output of an economy or an increase in GDP, it is about the fundamental transformation of a society and all the social and institutional fabrics within the society (Acemoglu 2012, 546). In the history of development and growth, the state has had defined roles as a promoter of economic growth, among them pushing the technological frontier by supplying a high-quality demand for production and goods (Reinert 1999, 283). An important argument to why capital flows should affect economic growth lies in the heart of investments and assets in the economy, the inflow of capital. With investments flowing into the economy assisting in developing new technology; expected production increases with both new and old technology, thus increasing growth and development in line with the conceptualizations of economic growth by Kuznets (Acemoglu 2012, 546–47). The mechanisms induced by advancing technology are self-reinforcing. The reason being, is that countries who gain high volume and experience in high-technology industries, can advance by lowering costs, increasing quality in production and shut out other countries, meaning that potential domestic growth also increases (Arthur 1990, 95). Further on, increased production brings additional benefits that are growth-stimulating, such as experience and education gains in the manufacturing process, as well as incorporating the learnings from production of a product or service to other sectors (Arthur 1990, 93).

The relationship between foreign capital inflow and domestic growth is also well-researched empirically, and propositions that foreign capital inflow is associated with higher overall capital-output ratios are well confirmed in literature (Voivodas 1973, 347). Mathematically, the relationship is specified positively on two premises by economists, namely that the actual foreign capital inflow is devoted to domestic capital formation, for instance investing in technology and production, and that the incremental capital-output ratio remains stable at the point of time when foreign capital inflow happens (Voivodas 1973, 345).

The two previous paragraphs have explained some mechanisms to economic growth induced by capital inflow, but as previously stated, capital flows are also about *outflow*, meaning domestic capital leaving for foreign economies as investments. First proposed in Keynes' general theory, the stock of capital is thought to increase by stately management and control of investments, whether to foreign or domestic economies (Crotty 1983, 59). Keynes (1933, 179) was not himself strictly positive to the outflow of capital, and referred to it as "… the penetration of a country's economic structure by the resources and the influence of foreign capitalists…", but still acknowledged that it would favor a country's capital output to invest in foreign resources and markets. As stated above, capital inflows favor domestic economies by freeing capital to advance technological solutions and production, but what are the growth-promoting mechanisms induced by capital outflow?

At least two mechanisms lie in the *expected returns* of investments. If a domestic economy invests into foreign assets and equities, one can expect that external debts are financed in one of two ways, **a)** through higher expected returns on external assets than liabilities, and **b)**, through the present value of future trade surpluses (Tille and van Wincoop 2010, 158). Both of these assumptions of capital outflow imply that the income streams induced by investing into foreign assets exceed the external debt, bringing in a steady stream of capital and equity that can be invested into the domestic economy, where, as with capital inflow, one would expect technological advancement and increased production. In a neoclassical perspective, it is also clear why capital flows and financial liberalization should affect economic growth. By improving risk sharing and allowing for higher capital outflows, you also decrease the cost of equity capital and therefore increase capital investments (Bekaert, Harvey, and Lundblad 2005, 4). There are also theoretical explanations to why alternative regulations and laws regarding investor rights and the quality of enforcement in domestic policies regulating capital flow in international finance are directly associated with growth (La Porta et al. 1998, 1115). The general take-aways from these theoretical contributions, is that liberalizing the equity market and increasing availability of foreign capital through law and regulations also reduces cost of external and internal finance by introducing better corporate governance in domestic economies, improving financial development, thus improving growth.

While capital flows in their absolute terms are highest between the advanced economies, because these are the economies best integrated into the economic markets and trade of the world, the mechanisms caused by capital flow are thought to have the highest impact on emerging markets (Koepke 2019, 516). Because capital flows are regulated to increase financial stability and development, exposed swings in the availability of foreign capital have un-stabilizing effects in emerging markets, as available capital in these markets is already scarce. This is also an argument to why policymaking and market differentiation is important in advanced economies when implementing capital controls that are restricting or liberating capital outflow as investments and loans to the emerging economies.

2.2.2 Why Economic Growth should be Unaffected by Capital Flow and Related Policies

According to Kenny & Williams (2001, 1), an article in *The Economist* stated that economic policies does not always relate to country growth. The empirical evidence for determinants of growth is seldomly unanimous, and often times, contradictory reports or research is published after inferences have been drawn from previous publications. Some suggestions to explain the unanimous inferences from statistical analysis of country growth is that the social world is of a more complex causal nature than economic models on growth are able to take into consideration (Kenny and Williams 2001, 2). There is also statistical evidence in research related to why increased capital flows through liberal financial policies should affect economic growth both negatively and positively. One negative effect is seen in Deveraux & Smith (1994), where they conclude that economic growth is affected negatively by financial liberalization and diversified portfolios in the world economy, because of reductions in precautionary savings, but that the diversifications caused by liberalization will always increase relative welfare.

2.3 Summary of Theory Chapter

The chapter started with conceptualizing the independent variables, where all the variables from the extracted data can be seen as a measure of or a regulation of capital flow, either as flow itself, or regulated by financial and economic policies through capital controls, visualized in figure 1. Further on, economic growth was defined broadly as improved economic welfare and expansion in productive capabilities, and with narrower definitions, such as the neoclassical. Some quick explanations of the common measurements of the independent and dependent variables in research are also provided, as well as the mechanisms related to capital flows and capital management on economic growth, thus why this is a relevant field of investigation in comparative politics.

Given that the meta-regressions are correcting for conceptualizations and measurements of variables statistically, we can use studies as units of analysis with different operationalizations of a given term, if they measure the same concepts. These procedures for correcting and comparing results are further explained in Chapter 3.

3 Method

The thesis asks "***How do Global Capital Flows Affect Economic Growth?***", and deems to assess it in three different questions to ensure all aspects of the research question is covered: *What is the mean observed effect of capital flow and capital flow management techniques on economic growth; Is there publication bias present in the published literature regarding the relationship; and What are the drivers or between-study characteristics that may or may not cause differences in the reported outcomes between the relationship of capital flow and capital flow management techniques on economic growth in literature?*

The thesis has taken an innovative standpoint in trying to answer the question of global flows effect on growth, and that is by comparing the statistical methods and results in a systematic review by frequentist linear fixed and mixed effects and Bayesian random effects meta-regression analysis. The chapter will first give defining concepts of what meta-regression analysis is – both in general, in a frequentist fixed and mixed effects manner and, in a Bayesian random effects manner, along with the continuous reasoning of why these methods have been chosen as the preferred alternative along with general strengths and weaknesses of the applied methods to the research question. Finally, the chapter chronologically presents how the analysis of this thesis has been conducted, along with different evaluations that have been conducted in order to ensure valid, reliable and robust interpretations of the findings and measures. A general summary of the chapter is presented at last.

3.1 Meta-Analysis

Meta-Analysis is regarded as one of the fundamental tools of organizing and synthesizing research as a systematic review due to extensive growth in the production of research across most disciplines, and can be conducted both non-statistically and statistically (Hedges and Tipton 2010, 909). Because of the differing outcomes in the sampled research on capital flow and management techniques' effects on economic growth, this approach could be fruitful to further synthesize the sampled research on the relationship, and thus help establish a greater research consensus on the topic, as well as providing nuanced assessments of the moderators that affect the reported outcomes. It is also a great tool for testing the different theoretical perspectives on how capital flows affect economic growth.

As meta-analysis and different approaches have been extensively developed since its first appearances in the 1970s as tools for systematic review among researchers (Stanley and Jarrell 2005, 301), there have become many different ways to conduct these kinds of analyses, and this thesis exclusively focuses on two different approaches which seldomly are combined and compared for research within the social sciences but rather within medical research, and thus provides an exciting and alternative outlook on meta-regression analysis within the field of political economy and comparative politics – a frequentist (linear) approach with fixed and mixed effects, and a Bayesian approach with random effects, which will be explained in further detail in the forthcoming chapters of the thesis after a general review of meta-regression in an analytical process.

3.1.1 Systematic Review – Quantifying Existing Published Literature

Because science is a cumulative process, and one therefore can find dozens and up to hundreds and sometimes thousands of studies addressing the same research questions or the same particular topics, researchers are increasingly conducting meta-analyses to aggregate and synthesize the literature on these topics (Viechtbauer 2010, 1). For meta-regression analysis, the systematic review consists of quantifying the relevant results from each study so that we can further aggregate and compare them in statistical regressions. It is a robust way of comparing quantitative research by analyzing the pooled results of studies – it is this statistical analysis that in fact is the "meta-analysis" (Walsh and Downe 2005, 205). The results or outcome measures that we quantify from the studies to conduct these regressions can come in many ways, including odds ratios, relative risks, risk differences, correlation coefficients – like this thesis bases most outcome measures on – and standardized mean differences. The most important thing is finding a measure of effect size that is quantifiable and standardizable across all the studies you are including in you review (Viechtbauer 2010, 1–2).

3.2 Meta-Regression Analysis in General – What Is It, and How Is It Conducted?

Meta-Regression Analysis (MRA) is in its shortest terms a regression of regression analyses. Contrary to traditional meta-analysis, which is closer to a literature review that summarizes the large literature on any given topic, and thus struggles to approximate unanimous consensus on a topic, MRAs potential to create scientific consensus is higher because it objectifies the review process and studies the processes that create and affect the published results or outcomes of any given paper (Stanley and Jarrell 2005, 299). In an MRA, the results or reported empirical outcomes of research are presented by numerical indices of effect size which then are summarized across the entire study population by one of many available statistical procedures, where one of the most important aspects is to use effect sizes that are comparable across studies

(Hedges and Tipton 2010, 909). Some advantages that comes from the analysis in an MRA contrary to a qualitative or traditional meta-analysis, is that MRA allows to investigate moderators both categorically in a univariate approach, along with semicontinuous variables such as country-scores, which in turn creates the option for more in-depth analyses of moderating effects (Hansen, Steinmetz, and Block 2022, 6). These moderating effects are also known as between-study characteristics, and they are thought to have an impact on how studies produce different results on an outcome measure of a dependent variable, therefore, these between-study characteristics must be included as covariates in the meta-regression. Such determinants or design elements of studies could include quantitative variables such as sample size and which time span the data covers, but should also include study characteristics which might be classified as more important, such as time-series or cross-sectional data, which data set that is used, the country or other geographical region studied and what method or equation that has been utilized to produce the coefficient that is presented in that study (Stanley and Jarrell 2005, 302–3). The investigations have to be conducted on empirical studies that identify determinants on some phenomena, and also produces some form of coefficient on the outcome variable we want to study (Stanley and Jarrell 2005, 302). The main objective of MRA is to generate a standardized effect size for all the units that have been included as units of data in the meta-analysis, which simply stated is done by summarizing regression results statistically in order to review the literature (Stanley and Jarrell 2005, 301). In regression models, also meta-regressions, we distinguish between models being "fixed effects", "random effects" and "mixed effects". In a fixed effect model, like the first frequentist linear model of this analysis, we assume that a single parameter value of the effects size is a common nominator across all studies, while a random effects/mixed effects model, like the second frequentist model and both Bayesian models of the thesis, assumes that the parameters of the studies follow some kind of distribution across the study units (J. P. T. Higgins, Thompson, and Spiegelhalter 2009, 137). In a scenario where we have a fixed effects model without any moderators, such as the first frequentist model of the analysis, we are really answering the question of the average true effect across all studies that are included in the analysis. The goal is to make a "conditional inference" only about the studies, not anything else (Viechtbauer 2010, 4). Random effects and mixed effects models are however different from fixed effects models, in that they provide the ability to draw unconditional inferences about a larger set of studies based on the set of studies that are included in the meta-analysis. So when the fixed effects model gives the answer to the true average effect size, the random effects and mixed effects model gives the answer to the true average effect size in a larger population of studies than what you originally have (Viechtbauer 2010, 4).

The main objective of a meta-analysis is to create a "synopsis of a research question or a field" (Jackson and Philips 2023, 2). This is by no means a small task and is best solved by dividing the objective into different steps and solving them step-by-step. In the context of meta-analysis, this concept is best described by using covariates to explore and explain substantial heterogeneity and define the differences between the existing empirical literature (van Houwelingen, Arends, and Stijnen 2002, 607). First, and maybe most importantly, is to identify the research question, as in all research. Thereafter, one must create a strategy to specify what articles and literature to include in the meta-analysis, often called inclusion or selection criteria. The process of avoiding publication bias is part of this second step, which the analysis in itself also helps determine in the research question it creates a synopsis of (Jackson and Philips 2023, 2). Besides assessing publication bias, MRA is also extremely efficient in disclosing studies where it is suspected that the authors have been p-hacking to force statistically significant results. P-hacking narrowly defined, denotes "conscious or unconscious manipulation of data or methods until statistical significance is achieved (Irsova et al. 2023, 7).

The third step after establishing scouting terms or inclusion criteria revolves around documenting your empirical findings in research through an own dataset in which each singular observation is a study-model, meaning a unit of data. At a minimum, the dataset must include coefficients, standard errors and degrees of freedom as variables from each piece of literature or observation (Jackson and Philips 2023, 2). Other quantities and variables that often are included in the dataset are authors, method, data and model-specific characteristics (publication type, year, data-coverage), which in turn are used to analyze the effects of moderators and examine the heterogeneity among all the studies (Jackson and Philips 2023, 2). As it is recommended to include more than just one estimate per study, an important notice is that you should also include at least one robustness check. You should also cluster standard errors at the study level (Irsova et al. 2023, 9).

When the dataset is finished, one can finally conduct the actual analysis, which is the final step besides actually interpreting and discussing the results that are produced. There are arrays of different types of meta-analyses, but this thesis focuses on the use of meta-regression analysis, known as MRA, where the dependent variable is the effect size, and the independent variables are the study-model factors (such as errors, sample size and data-coverage). This helps students and researchers alike to "identify the extent to which the particular choice of methods, design and data affect reported results" (Jackson and Philips 2023, 2). The effect size, which is the main objective of MRA, was defined by Glass as:

$$g = \mu_e - \mu_c/\sigma$$

where μ_e is the mean of the experimental group, μ_c is the mean of the control group and σ is the standard deviation of the control group (Stanley and Jarrell 2005, 301). The central idea of MRA is then that effect size is a standard measure of an empirical effect that can be assumed constant across all scouted literature in the dataset.

The variation in empirical effects explained by model-specific characteristics in MRA have been synthesized in a new formula building on the model of standard regression. The suggested model for MRA is then:

$$b_j = \beta + \sum_{k=1}^{K} \alpha_k Z_{jk} + e_j \qquad j = 1,2, \dots L.$$

where Z_{jk} is the meta-independent variable which measures model-specific characteristics in empirical studies and therefore explains its systemic variation from other results in the literature. b_j is the reported estimate (read: effect size measure) of β of the jth study comprised of L studies. α_k is the MR-coefficient reflecting the biasing effect of model-specific characteristics and e_j is the MR-disturbance term (Stanley and Jarrell 2005, 302). Some of the characteristics and design elements of the empirical literature that Z_{jk} measures besides those already mentioned as quantities and variables are for instance dummies reflecting plausible effect-manipulation in the existing research; sample size; author characteristics; measures of data quality; and specification variables that account for differences in functional forms, data definitions, types of regression etc (Stanley and Jarrell 2005, 302).

3.2.1 Comparing Effect Size Measures Across Study Units

As established in the previous section, showing to Hedges and Tipton (2010, 909), the effect size measures that are extracted from all the dependent and independent variables studies in the sample must be comparable. This, of course is difficult without using some kind of standardizing estimation on the measures, as the studies in the sample report effect sizes are derived by several different methods from econometric models to panel regressions which produces vastly different measures of estimates. To eliminate this problem, and thus create estimates from each study that are comparable no matter method, sample size, data or preferred measure used in the original studies, we turn to the solution of partial correlation coefficients (PCCs), which makes it possible to draw statistical inferences from the meta-regression models that have been used on a scale from negative one to positive one. To be very clear; this makes it possible to measure the effect or association of capital flow and capital flow management techniques on economic growth across all studies in our sample, unconditionally. Each and every study has reported at least one effect estimate on the relationship between the independent variable of their study and economic growth, and the degrees of freedom are given by n-1 to that given statistic, but the studies have varied in reporting standard errors or t-statistics as precision-measures to their coefficients. For studies who have not reported standard errors, the standard error is calculated by:

$$SE = \frac{c}{t},$$

where c is the extracted regression coefficient, and t is the related t-statistic to the coefficient. For studies who have not included t-statistics as precision measures, we can calculate these by:

$$t = \frac{c}{SE},$$

so that we have sufficient measures to calculate the partial correlation coefficients and their related standard error for the later regression analyses.

To calculate the partial correlation coefficient (PCC) r for each study, we use the formula by Stanley & Doucouliagos (2012, 24–25):

$$r = \frac{t}{\sqrt{t^2+df}},$$

Where t is the extracted t-statistic of our best-set regression coefficient, and df is the degrees of freedom (n-1) associated to this statistic.

When we have calculated the partial correlation coefficient, we can further on calculate the much-needed standard error of each partial correlation for our estimations by:

$$\varepsilon = \frac{\sqrt{(1-r^2)}}{df},$$

where ε is the standard error to each coefficient (Ahmadov 2014, 1245). When all the above measures have been calculated, we have sufficient information to input and fit to our model as parameters for comparable results in the equation.

3.3 Frequentist Meta-Regression Analysis

The first two models presented in the analysis are frequentist linear meta-regression models, which in its simplest form means that we are investigating the linear relationship between the standardized effect estimates, their standard errors and potential moderator variables (Viechtbauer 2010, 2). The first model is a fixed effects model, which is previously established as by Viechtbauer (2010, 4) and Higgins, Thompson and Spiegelhalter (2009, 137) to mean that we are only examining the true average effect size across the sample units, and not a bigger hypothetical sample like in a random effects model when no moderators are included in the model. The second model is a mixed effects model with moderators or between-study-characteristics, and based on the previous assumptions, we can draw inferences from the results on a larger population than only the study sample. Also, contrary to the common opinion among many researchers in literature, fixed effects does not mean that we assume that the true effects are homogenous as long as we restrict the inferences to the set of studies that are included in the regression models, and we can draw valid inferences from our results from these models as well (Viechtbauer 2010, 4). The inferences are thus conditional, and not unconditional as the ones we can draw from random effects and mixed effects models.

Based on the modelling and estimations of Viechtbauer (2010) in the R-package "metafor", our model fit starts with i = 1, …, k independent effect size estimates that each estimates a corresponding true effect size. Further on, we assume a function:

$$y_i = \theta_i + e_i,$$

where y_i is the designated observed effect in the i-th study, θ_i the corresponding (unknown) true effect, e_i is the sampling error, and $u_i \sim N(0, v_i)$. The equation assumes that y_i's are unbiased and normally distributed estimates of their responding true effects. It is also assumed that we know the sampling variance given by v_i. Because we have used PCCS to standardize the measured outcomes of each study, no further normalization has to be conducted to meet the assumptions of the model. When we add moderators or between-study characteristics to our model, the model by default becomes a mixed effects model, because we assume that we can account for at least part of the heterogeneity that is present in the "true" effects of the units in the sample. For the second frequentist model where several moderators are included, we therefore have a model given by:

$$\theta_i = \beta_0 + \beta_1 x_{ij1} + \cdots + \beta_{p'} x_{ip'} + u_i,$$

where x_{ij} denotes the value of the j-th moderator variable for the i-th study. For this mixed effects model, we now, contrary to the fixed effects model assume that $u_i \sim N(0, r^2)$, where r^2 denotes the total amount of residual heterogeneity among the true effects, meaning the variability in the true effects that are not accounted for by the between-study characteristics, meaning moderators, that we have included in the model. By this assumption, our main goal should be to determine how much the between-study characteristics influence the size of the average effect or "mean estimate" of the population. Also, because of our assumptions of *conditional* inferences drawn from fixed effects models versus *unconditional* inferences drawn from random effects models, we can draw more unconditional inferences from the second frequentist model on a larger hypothetical population than just the sampled studies.

3.3.1 Model Evaluations of the Frequentist Models

In the Frequentist Models, there are several tests and assumptions that we have to evaluate and meet to be able to draw valid inferences from the models. The conducted tests and evaluations that have been assessed in the Frequentist models are explained in this next section of the thesis.

3.3.2 Alternative Specifications

Alternative specifications simply refer to the fact that we input alternative specifications to our model, such as limiting the estimated parameters to a set of years as a measurement to ensure that the results are robust across different variations of data inputs – or alternative specifications of the model with different moderators than the entire set of characteristics. This ensures that the parameter estimates are robust to varying model fits.

3.3.3 QQ-Plots

In statistics, Quantile-Quantile (QQ) plots are used mainly to compare different distributions of data, where quantiles can be seen as “like-positioned values” of data entries. In this thesis, they are used in two of the more common ways, which is to compare the residuals from the frequentist models against an expected normal distribution, and also to help reveal potential outliers of the data units, with outliers meaning entries that differ from the “normal” (Marden 2004, 606). The plot is depicted by a straight (linear) regression line signifying a normal distribution of the theoretical quantiles, with individual plots for each sample quantile.

3.3.4 Leverage and Leverage Plots

An easy way to think about leverage in statistics is to think about how far away the independent values of an observation are from the independent values of other observations. In this meta-analysis, the observations are each study unit, so we can think of it as how far away the respective regression values from one study are from another one in the sample. When we have high leverage points on some studies, these studies can be interpreted as outliers with respect to the independent variables in our regression – that have the potential to cause large changes in the parameter estimates of the regression, meaning they are “influential” to the outcome estimates in linear regression models. The estimate of the influence is known as Cook’s distance (Cook 1977), and can help researchers determine which data points that should be checked for validity, and thus what study units of the meta-analysis that might be better to omit from the estimation to ensure more consistent and valid results.

3.3.5 Breusch-Pagan

The Breusch-Pagan test is a useful tool in statistics for identifying potential heteroscedasticity and random coefficient variation in frequentist linear regression models. An assumption we have of linear models is that of homoscedastic disturbances and fixed coefficients or moderators, and the BP-test helps us evaluate these assumptions so that we can consider potential losses in efficiency and biases in the estimated standard errors, which in turn could lead to invalid inferences (Breusch and Pagan 1979, 1287). In the context of linear regressions, homoscedasticity refers to constant variance across all levels of the independent variables, or that the spread or dispersion of the errors are consistent throughout the range of predictor values. The test can be visualized either statistically by showing the differences in numerical values of the predicted values vs. the residuals, or graphically in a plot of the residuals vs. predicted values, which is more easily interpreted to the naked eye and the non-statistical reader. In the plot, a symmetric pattern around zero suggests that the assumption of homoscedasticity is met, whilst a pattern of the data points fanning out, meaning that the spread of residuals increases or decreases as the predicted values increases indicates potential heteroscedasticity. Homoscedasticity is an important assumption in linear regressions, because it ensures that the estimated coefficients are unbiased and that we have correct estimations of the standard errors and valid confidence intervals.

3.3.6 Likelihood Ratio Test

The likelihood ratio test (LRT-test) is a quantitative approach to model comparison either between models or nested within a model. In an LRT-test, statistical hypotheses are formulated to compare the fit of two nested models: a simpler model and a more complex model. The null hypothesis states that the simpler model is sufficient, while the alternative hypothesis posits that the more complex model provides a significantly better fit. The test statistic, representing the ratio of the likelihoods of the data under the two models, is calculated, usually as the difference in log-likelihoods. Degrees of freedom are determined based on the difference in the number of parameters between the models. A significance level is chosen, typically 0.05 or 0.01, to evaluate the test. By comparing the calculated test statistic to the critical value from the appropriate chi-square distribution, a decision is made: if the test statistic exceeds the critical value, the null hypothesis is rejected, indicating that the more complex model is preferred; if not, the null hypothesis is not rejected, suggesting that the simpler model is sufficient. The results are interpreted accordingly, determining whether the additional complexity in the more complex model significantly improves the fit compared to the simpler model (Lewis, Butler, and Gilbert 2011, 157–58).

3.3.7 Wald Statistics

The Wald statistic is a way in statistical modelling to assess the significance of individual parameters within a larger regression model, which makes it possible to determine which ones of the predictor variables that are important contributors to the model. For this instance, only the second coefficient index, which is equivalent to the moderator variable "DataTSCS", a dummy for panel data, was tested in the frequentist mixed effects model with moderators. The Wald statistic is therefore a measure commonly applied in logistic regression and other generalized linear models. It assesses whether the coefficient of a predictor variable is significantly different from zero by comparing the square of the parameter estimate to its estimated variance. The statistic follows an asymptotic chi-square distribution with one degree of freedom. A large Wald statistic (> 1.96) indicates a significant effect of the predictor variable on the outcome, leading to the rejection of the null hypothesis, while a small statistic (< 1.96) suggests insignificance, and much like we use leverage tests to determine predictors of units, Wald tests help determine predictors of the parameters in a model across all units (Pawitan 2000, 54–56).

3.4 Bayesian Meta-Regression Analysis

For regression analysis in general, Bayesian regression is often recommended in situations where the sample is of limited size, like this thesis which has a total of seventeen sampled studies with one effect estimate from each study (Williams, Rast, and Bürkner 2018, 1, 3). Some of the advantages of Bayesian regression that appears in the presence of small sample sizes, is the fact that they ensure non-boundary estimates to ensure not producing too liberal statistical estimates for the summary effect, and also produces the full posterior distribution of R^2 (Williams, Rast, and Bürkner 2018, 3–4).

Another one of the advantages of Bayesian Meta-Analysis is how it more effectively can address research questions directly compared to for instance a frequentist approach and thus may be interpreted more intuitively (Röver 2020, 4).

To conduct the Bayesian Random Effects Meta-Regression Analysis of the thesis, the package "brms" in R has been the base of the regression. The Bayesian models are fit to the regression by the use of Hamilton Monte Carlo sampling (HMC), often referred to as hybrid Monte Carlo (Bürkner 2017, 5). The models are also fit as multilevel models (MLMs), meaning that we can measure modelling differences on both group-levels (author levels) and on the population-levels (our between-study characteristics) simultaneously (Bürkner 2017, 1). Sampling in Bayesian analysis simply refers to the sampling of data, in other words, iterating the data through chains in some programming language which creates a synthetic or computed "copy" of the input data in which we can test and analyze our moderator effects on. The sampled data thus creates a much larger and more robust data sample for us to assess the effects on, which gives more reliable results. The samples created by HMC-sampling are much less autocorrelated compared to other sampling-algorithms (Bürkner 2017, 5), where autocorrelation could be loosely be defined as:

> "… the property of random variables taking values, at pairs of locations a certain distance apart, that are more similar (positive autocorrelation) or less similar (negative autocorrelation) than expected for randomly associated pairs of observations." (Legendre 1993, 1659).

In other words, HMC-sampling eliminates that we get autocorrelation between variables of our data that in nature should be heterogeneous.

Derived from the model descriptions of the "brms"-package of R in Bürkner (2017) our Bayesian model at its core is given by:

$$y_i \sim D(f(n_i), \theta),$$

where the prediction of the response y comes from the linear combination of n-predictors transformed by the inverse link function f assuming a certain distribution D (also known as family) for y, stressing the dependency on the i-th data point of the estimation. θ describes additional family specific parameters, which for this analysis is omitted due to the fact that the model only inputs parameters that are evaluated on group-levels and population-levels.

The linear predictor of the model can be written as:

$$n = \boldsymbol{X}\beta + \boldsymbol{Z}u,$$

where β are the coefficients given at the population-level and u are the coefficients given at the group-level. The response previously defined as y make up the data along with **X** and **Z**, and β (fixed effects), u (random effects) and θ are the model parameters which are estimated in the computation.

In Bayesian regression, it is common to set very strong priors, and even though "brms" allows us to specify the priors of the models at very strong levels this has not been done. Based on the findings in Willams, Rast & Bürkner (2018, 1), weakly-informative priors in a meta-analytic scenario with Bayesian modelling and small sample sizes like this thesis actually better maintain consistent error rates and better captures between study-variability. Overall, the performance of Bayesian models in these scenarios are better with weakly-informative priors, and that is why this has become the chosen approach to the Bayesian regression models of this thesis, due to a limited sample of seventeen studies.

3.4.1 Model Evaluations of the Bayesian Models

In the Bayesian models, there are several tests and assumptions that we have to evaluate and meet to be able to draw valid inferences from the models. The conducted tests and evaluations that have been assessed in the Bayesian Models are being explained in this next section of the thesis.

3.4.2 R-Hat Values

In Bayesian analysis, the Gelman Rubin diagnostic, also known as the r-hat value, is a diagnostic tool for assessing convergence and variance – meaning adequate sampling of our data (Conner et al. 2016, 555). Usually, r-hat values < 1.1 signifies convergence, and values closer to or equal to 1 are stronger indicators of convergence. It has been recommended that simulations of the data are terminated when parameters in either level of the model exceeds r-hat values of 1.1. The diagnostic value is calculated as the square root of the ratio of two estimators for the target variance (Vats and Knudson 2021, 518).

3.4.3 ROPE

In frequentist statistics, we use estimates of p-values to reject or accept null values of parameters. The equivalent to this in Bayesian statistics are ROPE-tests (region of practical equivalence) indicated by the HDI of the posterior distribution (Kruschke 2018, 270). ROPE has been referred to and given the notion as both the “good-enough belt” and the “smallest effect size of interest” among other things in earlier statistical literature and refers to an interval around the null value of a parameter. The ROPE-test used on parameters gives us a percentage of how much of the 95% HDI falls inside or outside the null value to that specific parameter (Kruschke 2018, 272). Based on the percentage of how much of the HDI falls inside the ROPE, Kruschke (2018, 272) has provided a general framework on how to accept or reject parameters for practical purposes in the interpretations of Bayesian models:

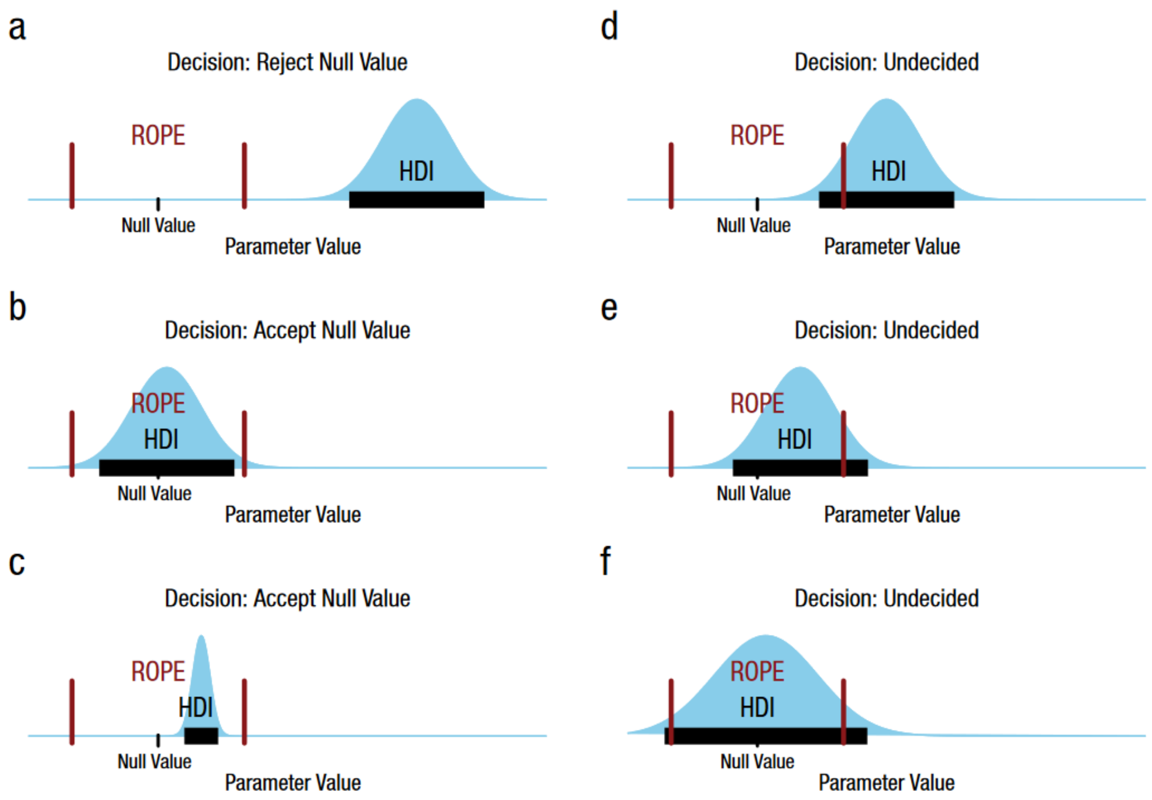


Figure 2 *Decision-Making When Assessing the ROPE-test. Source: Kruschke (2018, 272)*

3.4.4 Pooled Effects

To examine the results of the Bayesian meta-regressions, forest plots have been modelled of the pooled effects of the standardized mean difference (summary statistic) to both Bayesian regressions to better visualize the effects on group-levels. In Bayesian regression, a forest plot of pooled effects of the standardized mean difference would usually display study labels for the data of the meta-analysis, estimated effects shown by point estimates of the standardized mean difference, 95% confidence intervals around the estimated effect size and an overall pooled measure of standardized mean difference across all studies (J. P. Higgins and Deeks 2008).

3.4.5 Prior Knowledge and Posterior Distributions

Bayesian analysis start with assumptions of the prior knowledge, which are expressed as "… a distribution on the parameter space and updates the knowledge according to the posterior distribution given the data." (Ghosal 1997, 1). What we essentially are looking for is regarding prior knowledge and posterior distributions is that the knowledge gained from our posterior distributions increases as we iterate (sample) the data more and more and get a bigger hypothetical sample, which ensures that consistency is present as a benchmark-interpretation within the model.

3.4.6 Bulk and Tail ESS

Effective Sample Size (ESS) is in Bayesian MCMC and HMC sampling a term used to explain the effective sample size by capturing how many independent draws contain the same amount of information as the dependent sample of the algorithm in our model. The higher the ESS is relative to the initial sampling, the better (Vehtari et al. 2021, 272). For reference, both Bayesian regression models of this thesis are run in 4 chains of 4000 iterations each, with a post-warmup sample of 2000 that totals to 8000 draws of the post-warmup sample. When considering the ESS, 8000 is therefore the sample size we assess it relative to. Along with the r-hat values and ROPE-tests previously explained, we use the ESS as a measure to where it needs to be "large enough" for us to draw valid inferences (Vehtari et al. 2021, 272). The terms "Tail" and "Bulk" refer to different estimations of the effective sample size in the sampled distribution of quantiles. The tail-ESS refers to the effective sample size in the 5% outer portions of our distribution, while the bulk-ESS refers to the inner center 95% of the sample distribution. Together, they are effective measures of ESS across the entire distribution of sampled data.

3.4.7 R^2 and Bayes R^2

In frequentist regression analysis, the classical R^2, also known as the squared multiple correlation or the coefficient of determination can be written as:

$$R^2 = 1 - \frac{Var(z)}{Var(x)} \text{ or } R^2 = \frac{V_{n=1}^{N} \,{}^\wedge Yn}{V_{n=1}^{N}\, Yn},$$

which in practice measures how much of the total variability of the outcome on the dependent variable is explained by the independent variable and the potential moderators in our regression model. An R^2 of for instance 0.6, would indicate that 60% of the total variability in reported effect sizes of our study unit is explained by the model – or as an easy-to-understand way on how the model explains the data (Jöreskog 1999, 1; Gelman et al. 2019, 307). In Bayesian regressions, we have a similar, but different determinant known as the Bayes R^2. Since Bayesian regression operates in a framework of posterior distributions, the Bayes R^2 can be written as:

$$Bayes\ R^2 = 1 - \frac{Posterior\ mean\ of\ residual\ variance}{Posterior\ variance\ of\ the\ outcome\ variable} \text{ or}$$

$$Bayes\ R^2 = \frac{Explained\ variance}{Explained\ variance + Residual\ variance},$$

which creates a similar measure as in the classical R^2, but this time for interpreting how much of the variance in the posterior distribution of the model is explained by the data (Gelman et al. 2019, 307–9).

3.4.8 ETI and HDI

Highest Density Intervals (HDI) in Bayesian estimations refers to the summary of a range of the most credible values of a measurements, and is comparable to credible or confidence intervals in frequentist statistics that explains certainty in measures of parameters (Kruschke 2018, 270). In other words, HDI is the interval where values of a given parameter most likely finds itself. When interpreting HDIs, parameter values with higher densities are considered and should be interpreted as more credible than parameter values with lower densities – a 95% HDI would then refer to the 95% most credible values of the parameter.

The other method of computing credible intervals in Bayesian analysis is known as Equal-Tailed Credible Intervals (ETI). This interval is defined such that "… equal probability is observed below the lower limit and above the upper limit of the interval" (Joshi et al. 2023, 639–40), and creates another credible interval for us to compare to the HDI, which if everything is calculated correctly gives us comparable intervals, so we can make sure that the measurements of the parameters in our model are acceptable within the ranges of both.

3.4.9 Posterior Predictives

In Bayesian analysis, the posterior predictive, also known as the posterior predictive distribution, is the distribution of the possible unobserved values conditional on the observed values. Explained in a more common-sense language, it refers to the range of possible outcomes we might expect to see for something we have not observed yet, based on what we already observed given by our data. Say for instance in this thesis, the data inputs the reported effect sizes of an empirical relationship of seventeen studies. The posterior predictive distribution then helps us estimate what we might see as a reported effect size of a completely new, unpublished study given the information we have on the studies we have sampled for the model.

3.5 Why do Researchers Conduct Meta-Regression Analyses?

3.5.1 General Strengths and Weaknesses of Meta-Regression Analysis

One of the disadvantages of traditional meta-analytic approaches is that they are flawed by design, and at their core are unable to account for both effect heterogeneity and reporting bias, and that studies utilizing the traditional approach often can report estimates that are strongly inflated by publication bias, and that Bayesian bias models are better at producing "true" effect sizes of the estimates (Cools, Finseraas, and Rogeberg 2021, 989). Now, Bayesian approaches to meta-analysis are nowhere near being new in statistical modeling. In fixed effect and mixed effect models, Bayesian approaches developed as technical developments of meta-analysis as early as the 70s and 80s through Empirical Bayes estimation. Rubin, Raudenbush and Bryk called their new approach empirical Bayes meta-analysis because their method used the data at hand to estimate the prior distribution of the residuals in their model (Tipton, Pustejovsky, and Ahmadi 2019, 163).

Several general strengths of both frequentist and Bayesian MRA have been identified in previous sections of this chapter. In general, Bayesian regression shows strengths by addressing research questions more intuitively than other types of regression because it is more effective in creating valid inferences of larger populations, and also that it ensures not producing too liberal estimates of summary and parameter effects (Williams, Rast, and Bürkner 2018, 3–4; Röver 2020, 4). For MRA in general, it poses many strengths. First, it allows us to compare and evaluate a large amount of research no matter how outcomes are measured or methods utilized in that specific research (Viechtbauer 2010, 1–2). Compared to traditional or qualitative meta-analysis, it also allows for investigating moderators or between-study characteristics as well as semi-continuous variables, allowing for more advanced analysis of moderator effects (Hansen, Steinmetz, and Block 2022, 6). It also allows us to generate a standardized effect size across all study units in the data, meaning we can more precisely say what the actual effects of an independent variable is on a dependent variable, in this case, it allows to more precisely say what the actual effects of capital flows are on economic growth (Stanley and Jarrell 2005, 301).

One of the obvious flaws of meta-regression analysis compared to other types of research designs, is that it does not allow for comparing and estimating the effects of competing conceptualizations and measures of different terms to a dependent variable.

3.5.2 How to Answer Questions with MRA

Answering research questions using MRA involves synthesizing findings from multiple studies to identify patterns and associations across a body of literature as per chapter 3.1.1. The method allows us to explore the relationship between various factors (such as study characteristics, moderators, or contextual variables) and the outcomes of interest. By quantitatively examining these relationships, MRA provides insights into the magnitude and direction of effects, as well as the sources of heterogeneity in study findings. This approach enables researchers to draw more robust conclusions and identify potential areas for further investigation. Traditional research questions, such as “What are the drivers of” dependent variables cannot be answered through these types of analyses, but it can help understand the complexity and diversity of already researched empirical relationships in literature.

3.6 Descriptive Statistics as Trend-Investigation

3.6.1 Publication Bias

The most common way to address the question of publication bias in meta-regression analysis – which is an assumption that significant or positive results are systematically published rather than insignificant results – is by constructing funnel plots. The funnel plots in this contexts are constructed as scatter plots of each effect estimate from the studies against a measure of the precision - but only for the frequentist linear models - which most commonly is the standard error to each study estimate (Mavridis and Salanti 2014, 30).

To do a full analysis of the funnel plots, there are several things to consider. First, asymmetry (which is seen by high levels of standard errors in the plots), can be an indication of publication bias, but asymmetry also has alternative explanations such as heterogeneity, selective outcome reporting and random chance. In the absence of bias, funnel plots should resemble a symmetrical inverted funnel, whilst in the presence of publication bias in our data, the plots often appear skewed and asymmetrical (Egger et al. 1997, 629). Second, assessments of publication bias should be done on effect estimates from at least ten studies in order to obtain sufficient visual interpretations and inferences from the plots. Third and last, inferences drawn from funnel plots are much stronger when contours of statistical significance are added, such as an Egger's test, because it helps distinguish asymmetry from other causes, such as heterogeneity (Mavridis and Salanti 2014, 30). To avoid misleading inferences, the Egger's test was therefore developed as a supplement to traditional assessments of funnel plots to detect bias. The main outcome measure of the test is the degree of funnel plot asymmetry as measured by the intercept from regression of standard normal deviates against the precision of each deviate (Egger et al. 1997, 629).

The test is defined as a regression equation:

$$SND = a + b * precision,$$

where SND equals the standard normal deviate defined as the effect estimate divided by its standard error regressed against the estimate's precision. The slope, defined as b, will indicate the size and direction of the publication bias effect whilst a is a measure of the asymmetry where a deviation further away from zero indicates stronger asymmetry. The precision will mainly vary by the original studies' sample sizes. Because meta-analyses generally have smaller sets of trials which limits statistical powers of such tests, evidence of asymmetry is based on $P < 0.1$ (Egger et al. 1997, 929–30).

3.6.2 Modelling Heterogeneity

One of the flaws of empirical studies that must be assessed is the fact that they are heterogeneous in nature: they usually do not share the same sample characteristics and measures. How we assert inference when conducting meta-analyses then depends on how we assess between-study characteristics to estimate the summary effect of the studies. Using random effects models allows for exactly this – calculating average effects while accounting for between-study variance to generalize inferences on the topics we are studying (Williams, Rast, and Bürkner 2018, 2).

An assumption of homogeneity, meaning that we have an assumption of the existence of a common effect across all the study units, is rarely a just assumption for studies within the social sciences – because they seldomly share the populations that are addressed empirically, as well as the reported outcomes on the empirical relationship that we study (J. P. T. Higgins, Thompson, and Spiegelhalter 2009, 137). As established above, one of the main aims of MRA is to investigate the heterogeneity between reported effects of an empirical relationship in literature while simultaneously testing for the effects on the outcome by potential moderator variables, also known as predictors or between-study characteristics (Hansen, Steinmetz, and Block 2022, 6).

Several studies within the social sciences go far beyond the needs in exploring, examining and interpreting how heterogeneity affects empirical relationships in meta-analyses. One example within the social sciences is from Ahmadov (2014), which investigates the relationship between the extraction of oil and democracy levels, and another example is from Yesilurt & Yesilurt (2019), which examines the relationship between military expenditures and growth.

The analysis in the study of oil and democracy extends to exploring heterogeneity in the reported results. Ahmadov recognizes that divergent outcomes may stem from real-world factors and differences in the research process. Multiple versions of a basic model are calculated to explore partial effects, considering factors such as data characteristics, specification differences, regional and time dummies, and estimation characteristics. Two models, Fixed-Effect (FE) and Random-Effect (RE), are utilized, allowing for nuanced insights into the synthesis of study findings by considering both methodological nuances and real-world variations (Ahmadov 2014).

In summary, Ahmadov's meta-analysis offers a comprehensive understanding of the oil-democracy relationship, systematically addressing heterogeneity in study findings and providing nuanced insights into the empirical scholarship on this topic (Ahmadov 2014). Summary statistics reveal substantial heterogeneity in reported effects, with positive and statistically significant estimates dominating.

In a study examining the impact of military expenditure on economic growth, the article acknowledges a substantial literature, including both quantitative and qualitative approaches. The focus is on quantitative studies reporting an estimate of effect sizes, leading to the inclusion of 554 estimates from 91 studies. The methodological landscape is characterized by significant heterogeneity in data, theory, and econometric approaches, posing challenges for meta-analysis (Yesilyurt and Yesilyurt 2019).

3.7 Guiding Further Research

Based on the results given by the assessments of publication bias and heterogeneity in chapter 5 “Results” of the sampled metadata of existing research on the effects of capital flow and capital flow management techniques on economic growth, we can discuss the results and inferences induced by the analysis, and thus propose relevant considerations and actions that should be taken in the research on the topic to help provide research consensus.

3.8 Summary of Method Chapter

In this chapter, meta-analysis has been presented as a vital tool for synthesizing research, which offers both statistical and non-statistical approaches. Given varied outcomes in studies on capital flow and management techniques' effects on economic growth, meta-analysis could consolidate this research, fostering consensus. Meta-regression analysis (MRA), a regression of regression analyses, explores moderators systematically, offering advantages over traditional meta-analysis by objectifying the review process and between-study characteristics influencing reported results, and therefore accounting for heterogeneity. Conducting a meta-regression involves identifying the research question, specifying the inclusion or selection criteria, documenting the empirical findings, and analyzing the results. In the frequentist meta-regression analysis of the thesis, fixed and mixed effects models are used to examine average and population-wide effects, respectively, with evaluations ensuring robustness and validity. To add some fruitful innovation to MRA within the social sciences, Bayesian meta-regression analysis is compared to the frequentist analysis and is added due to the limited sample size of seventeen studies, which offers advantages such as non-boundary estimates and full posterior distributions of the explained variance.

4 Data

This chapter first presents the selection criteria along with the specific selection process of the data that is used in the MRA of the thesis, and also the process of how coefficients have been extracted from the units through a best-set extraction process. Tables of both the main dataset with extracted coefficients and units and converted PCC-measures, as well as descriptive statistics of the moderator variables or between study-characteristics are presented to be transparent of the data and give some insights to the reader on the dispersion and spread of data[2].

4.1 Selection Criteria

In order to make a meta-analysis add value to the field of research, the writer should always understand the topics that the research revolves around thoroughly in order to add value. Such values, that to some extent are discussed, include assessing publication bias and heterogeneity that other published articles do not (Irsova et al. 2023, 3).

One approach to choosing which articles to include in a dataset in an MRA, could be to choose five primary studies on the topic that encompass large parts of the research, and then generate a search query or scouting terms to use in databases such as Google Scholar based on central keywords that are repeated in those studies (Irsova et al. 2023, 3). In this thesis, which is an MRA, one should include at least ten studies, but the goal should be more than the minimum amount. When speaking of the statistical models, technically, only three studies are needed to conduct the analysis. In this thesis, all effect sizes in the empirical studies that are extracted for the meta-dataset must therefore be quantitative, meaning that some sort of statistical method must have been applied to a set of data in the original studies where a quantitative estimate of the effect of the relationship is presented (Irsova et al. 2023, 3–4). Studies should be included from all types of journals and no matter the quality of the study itself. If one suspects that studies are of relative poor quality compared to the rest of the dataset, it is possible to conduct subsample analysis to disclose how the exclusion of certain studies affect the results or not (Irsova et al. 2023, 4). To ensure that no important primary studies are excluded, the search query should also build on “snowballing”, in that the author should gather

[2] Raw datafile and R-code is available as supplementary files to the thesis. All studies included as data in table 1 and mentioned in “Dataset” are referred in the literature of the thesis.

the most referred articles from a set of primary studies and make sure that the ones that are most cited are not left out of the data (Irsova et al. 2023, 4).

The study selection process of this thesis was long and extensive, mainly because relevant literature on the initial empirical relationship was scarce and hard to navigate. That first relationship was that between capital controls and economic growth within political and economic literature, because the introductions and removals of capital controls has been a big part of liberal economic policy in world economic history. In order to find studies on this relationship, combinations of "Capital Control", "Economic Growth", "Regression" and "Regression Analysis" were used as search terms in Google Scholar. Google Scholar was the chosen database for searches, first, because it provides comprehensive coverage of scholarly literature across most all disciplines, and second, because it is easily accessible for others, making statistical replications of the analysis and extraction of data easier for others.

The initial search in Google Scholar did not return enough studies where the estimates could be extracted and converted to partial correlations using only the conceptualization of strictly "Capital Controls", because most studies used individual measurements of capital controls, and not a conceptualization and measurement of capital control itself. To provide enough studies to conduct the MRA, I had to be creative regarding the concepts. Google Scholar also provides readers with filtering abilities, such as the exclusion or inclusion of specific terms, as well as abilities to filter for publication years and other specific parameters.

As the theory has conceptualized, capital controls are only one of the measures of capital flow restrictions or management techniques in liberal economic policy, and capital flow is measured by many different parameters in economic literature. By searching for relevant literature in the initial three studies on capital controls, I was able to snowball my way into including capital flow, capital openness, financial liberalization, capital account liberalization, stock market liberalization and foreign direct investment (FDI) as other measures of the independent variable where economic growth still was the dependent variable of the studies. So, "Capital Flow", "Capital Openness", "Financial Liberalization", "Capital Account Liberalization", "Stock Market Liberalization" and "Foreign Direct Investment" were introduced as additional search terms along with the initial four. These terms are theoretically fitting to the research question, as conceptualized in chapter 2. Only studies written and published in English were used, mainly to avoid misinterpretations of concepts and measurements across studies. Studies were also included no matter the perceived quality, either by citations or other quality measures such as which journal the article was published in, working paper or full-on research article. This amounted to the sampling of twenty total studies, but three studies were dropped because I was not confidently able to estimate PCCs for the extracted estimates.

As established in the methods-section, all results must be comparable. Since PCCs have been used to standardize the results, both studies that have utilized econometric-type models and regression models to estimate parameter measures could be included as data, as long as the studies provided the necessary estimates for calculations of the PCC.

4.2 The Study Estimates Extraction-Process

The "best set" of parameter estimates is a selection process of the reported estimates that is frequently used in meta-analysis of economic parameters, as in this thesis (Viscusi 2018, 205). Most studies provide more than only one measure or estimate of the relationship between their independent and dependent variables, and a way of going around complex all-set datasets, where all relevant estimates from a study is included as data for a meta-analysis, is to utilize best-set estimates. The best-set estimates extraction process relies on a way of thinking where one judges what ought to be the best estimate of a study to use in a meta-analysis in order to give the best outlook of the parameters regarding the research question, therefore, only one estimate of the reported effect is included per study (Viscusi 2018, 205–6). This of course raises some questions regarding bias, which in this context is referred to as "best estimate selection bias". Regarding the nature of the thesis and how the meta-analysis attempts to capture very specific conceptualizations of the independent variables from each study, it has been chosen as the preferred option to ensure that the estimates only measure exactly what we are looking for regarding the research question and theoretical mechanisms of flow and growth. The potential downsides to best estimate selection bias induced by the best set-extraction process have been concluded to be lower than the potential downsides related to an all-set extraction process and the possibility of computing inconclusive results due to the very specific measures we are looking for.

4.3 Dataset

The sampled dataset in table 1 of this thesis consists of a total of seventeen studies in the period of 1994 to 2022 that investigates the empirical relationship between capital flow or capital flow management techniques induced as policies and economic growth in different geographical regions of the world, a total sample period of 28 included years, where each unit has one reported estimate on the effect of the relationship. The different conceptualizations of the independent variables that have been included as measures are capital flow, capital openness, capital control, financial liberalization, capital account liberalization, stock market liberalization and foreign direct investment (FDI). The dataset is not supplemented by or inspired by any other existing dataset but created by the basis of the main research question of the thesis. There is a total of sixty unique variables in the full dataset developed in R, providing us with an amount of 1020 data entries combined.

Author(s)	***Method/Model***	***Best Set Coef.***	***Best Set St. Error***	***Best Set DoF***	***Partial Correlation Coefficient (PCC)***	***t-statistic to PCC***	***Standard Error of PCC***
(Ayhan Kose, Prasad, and Terrones 2009)	*Panel Regression*	***0.07373***	*0.03547*	*251*	***0.130089***	*2.0787*	*0.003981557*
(Baharumshah and Thanoon 2006)	*Dynamic Generalized Least Squares (DGLS)*	***1.037***	*0.066*	*7*	***0.986117***	*15.7121*	*0.14254566*
(Ben Naceur, Ghazouani, and Omran 2008)	*Panel Regression*	***0.086***	*0.027*	*10*	***0,709654***	*3,1852*	*0,099963543*
(Borensztein, De Gregorio, and Lee 1994)	*Panel Regression*	***0.8438***	*0.4820*	*68*	***0.000021***	*0.0002*	*0.012884871*
(Chanda 2003)	*Cross-Sectional Regression Model*	***-1.11***	*0.64912*	*81*	***-0.186661***	*-1.71*	*0,009391185*
(D. P. Quinn and Toyoda 2008)	*OLS*	***0.377***	*0.419*	*466*	***0.041644***	*0.8998*	*0.001948648*
(D. Quinn 1997)	*Cross-Sectional Regression Model*	***0.3***	*0.141*	*57*	***0.271250***	*2.1277*	*0.017368589*
(Dar and Amirkhalkhali 2003)	*Random Coefficients GLS*	***-1.328***	*0.1490*	*18*	***-0.902921***	*-8.9128*	*0.0549354*

(Durham 2004)	*Panel Cross-Section*	***-0.027***	*0.028*	*48*	***-0.137854***	*-0.9643*	*0.020825165*
(Eriş and Ulaşan 2013)	*Bayesian Regression Model*	***2.369***	*0.57780*	*84*	***0.408350***	*4.1*	*0.009716409*
(Hamdaoui, Ayouni, and Maktouf 2022)	*Panel Regression*	***1.549***	*0.3013*	*48*	***0.595905***	*5.1411*	*0.019865196*
(Huang and You 2019)	*Two-Lender Three-Period Small Economy Model*	***0.212***	*0.19*	*743*	***0.0409***	*1.1158*	*0.001321378*
(Khan, Arif, and Raza 2021)	*Econometric Model*	***0.271***	*0.03939*	*53*	***0.686853***	*6.88*	*0.018853281*
(Mehic, Silajdzic, and Babic-Hodovic 2013)	*Panel Ordinary Least Squares (OLS)*	***3.124***	*0.473*	*51*	***0.678977***	*6.6047*	*0.017275734*
(Musila and Yiheyis 2015)	*OLS*	***-0.009***	*0.00283*	*26*	***-0.529534***	*-3.1830*	*0.038461384*
(Sakyi, Villaverde, and Maza 2015)	*DOLS*	***0.17***	*0.005*	*114*	***0.954063***	*34*	*0.00877182*
(Satyanath and Berger 2007)	*Panel Cross Section*	***0.000421***	*0.0015*	*83*	***0.030793***	*0.2807*	*0.012048179*

Table 1 *Dataset with Study Units, Method, Extracted Coefficients and PCC-Measures*

Originally, the dataset consisted of twenty studies, but among these twenty, three studies had to be removed for the purpose of having a full dataset where all units had standardized measures of effect size and standard errors. The studies of Aizenman, Jinjarak, and Park (2013), Klein (2005) and Eichengreen and Leblang (2003) were ultimately dropped due to not being able to confidently calculate and determine standard errors of the PCC-measures that were within the expected value range. The original dataset had measures of twelve between-study characteristics that could be extracted and collected for the analysis. These characteristics were the author(s) of the study, the method or model that was used in the original study, type of data (TSCS or TS), the publication year, publication type, period of data coverage, journal that the original study was published in, sample size in original study, reported statistical significance, political scientist or economist writer, conceptualization of the independent variable and a dummy for the conceptualization “Capital Control”.

4.4 Variables

In table 2 are descriptive statistics of all the variables that have been used as moderators in the MRAs. The table shows the variable name and type, where the variable-type is character for “Author”, and numerical-type variables for all the other ones. Variables “DataTSCS”, “TypeArticle”, “Significant”, “Pol_Sci” and “Capital_Control” are all dummy variables of the initial codings in numerical values 0 and 1, while variables “Year”, “n” and “time_span_years” are numerical values showing the publication year, sample size and time span of data respectively. The table also shows the frequency of each value for the dummy variables, and the number of distinct values to each variable for the numerical variables. To each variable is the mean value with the related standard deviation, as well as the minimum and maximum values to each variable. As we can see, there are no missing values for any of the moderators. For instance, we can see that the mean study unit is published in ca. 2009, with the median in 2008, and that only one study uses TS-data as opposed to TSCS-data as the basis of their empirical analysis. The average study has a sample size of 91.6, and a median of 58, meaning that a few studies are aggregating the average sample size value with uncommonly high samples of data. Three studies use “Capital Control” as their conceptualization of the independent variable, and only one study is written mainly, or only by a political scientist. The average time span of a data sample is 26.1 years, while the median is 27 years. To each variable is an interquartile range (IQR), which refers to the mid-spread (50%) of parameter values between the 25th and 75th percentile range.

All of these variables from table 2 have been manually coded based on the information provided by each study unit, and further developed and recoded to be part of the dataset. “Author” is solely a replication of the names of the authors. “DataTSCS” was developed as a dummy in R based on a variable with codes TS and TSCS signifying type of data. “Year” is the publication years provided. “TypeArticle” was coded as a dummy like “DataTSCS”, based on codes of article or working paper. “n” is the extracted sample size to the model where the best-set extraction coefficient is from. “Significant” was coded similar to the previous dummies, and the same goes for “Pol_Sci” and “Capital_Control”, where each variable had codes for different categories of the variable which were transformed to dummies. “time_span_years” was developed by subtracting the first year of data to the last year of data of each given model, where date and month was taken into consideration.

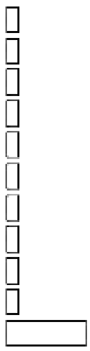
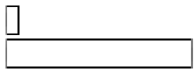
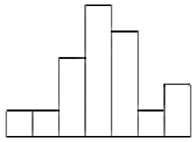
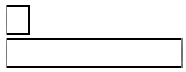
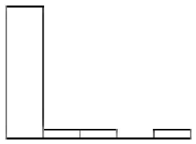
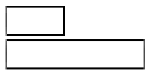
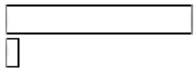
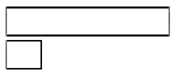
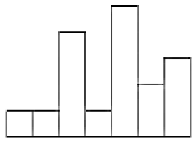
No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	Author [character]	1. Baharumshah & Thanoon 2. Ben Naceur et al. 3. Borensztein et al. 4. Chanda 5. Dar & Amirkhalkhali 6. Durham 7. Eris & Ulasan 8. Hamdaoui et al. 9. Huang & You 10. Khan et al. [7 others]	1 (5.9%) 1 (5.9%) 1 (5.9%) 1 (5.9%) 1 (5.9%) 1 (5.9%) 1 (5.9%) 1 (5.9%) 1 (5.9%) 1 (5.9%) 7 (41.2%)		17 (100.0%)	0 (0.0%)
2	DataTSCS [numeric]	Min : 0 Mean : 0.9 Max : 1	0 : 1 (5.9%) 1 : 16 (94.1%)		17 (100.0%)	0 (0.0%)
3	Year [numeric]	Mean (sd) : 2009.2 (7.9) min ≤ med ≤ max: 1994 ≤ 2008 ≤ 2022 IQR (CV) : 11 (0)	13 distinct values		17 (100.0%)	0 (0.0%)
4	TypeArticle [numeric]	Min : 0 Mean : 0.9 Max : 1	0 : 2 (11.8%) 1 : 15 (88.2%)		17 (100.0%)	0 (0.0%)
5	n [numeric]	Mean (sd) : 91.6 (111.5) min ≤ med ≤ max: 8 ≤ 58 ≤ 467 IQR (CV) : 35 (1.2)	16 distinct values		17 (100.0%)	0 (0.0%)
6	Significant [numeric]	Min : 0 Mean : 0.7 Max : 1	0 : 5 (29.4%) 1 : 12 (70.6%)		17 (100.0%)	0 (0.0%)
7	Pol_Sci [numeric]	Min : 0 Mean : 0.1 Max : 1	0 : 16 (94.1%) 1 : 1 (5.9%)		17 (100.0%)	0 (0.0%)
8	Capital_Control [numeric]	Min : 0 Mean : 0.2 Max : 1	0 : 14 (82.4%) 1 : 3 (17.6%)		17 (100.0%)	0 (0.0%)
9	time_span_years [numeric]	Mean (sd) : 26.1 (9) min ≤ med ≤ max: 9 ≤ 27 ≤ 40 IQR (CV) : 13 (0.3)	12 distinct values		17 (100.0%)	0 (0.0%)

Table 2 *Descriptive Statistics of the Moderator Variables in the Dataset*

5 Results

5.1 Descriptive Statistics

First, to give some indications on both the spread of studies included as data, as well as their reported effects and the visual trends of the relationship, there is provided one plot in figure 3 displaying a timeline of the publications, as well as two graphs of the reported effects by year converted to Partial Correlation Coefficients (PCCs), where the first graph shows all reported effects in figure 4, and the second graph in figure 5 shows the yearly average reported effect. The reported effects are the reported effects on the outcome variable of the studies, economic growth, by the capital flow or management technique assessed in each study. The PCC-value has been provided as a standardized measure of the reported effect outcomes in the Methods-section ranging from negative 1 to positive 1, providing comparable measures of all reported outcomes.

As we see in Figure 3 of publications over time, there's a good spread of yearly publications, ranging from the years 1994 to 2022, covering an extended period of time in academia. The years 2003, 2008, 2013 and 2015 have two publications per year, while the other included years have one publication a year. In the period from 1994 to 2022, we are missing publications for the years 1995, 1996, 1998, 1999, 2000, 2001, 2002, 2005, 2010, 2011, 2012, 2014, 2016, 2017, 2018 and 2020.

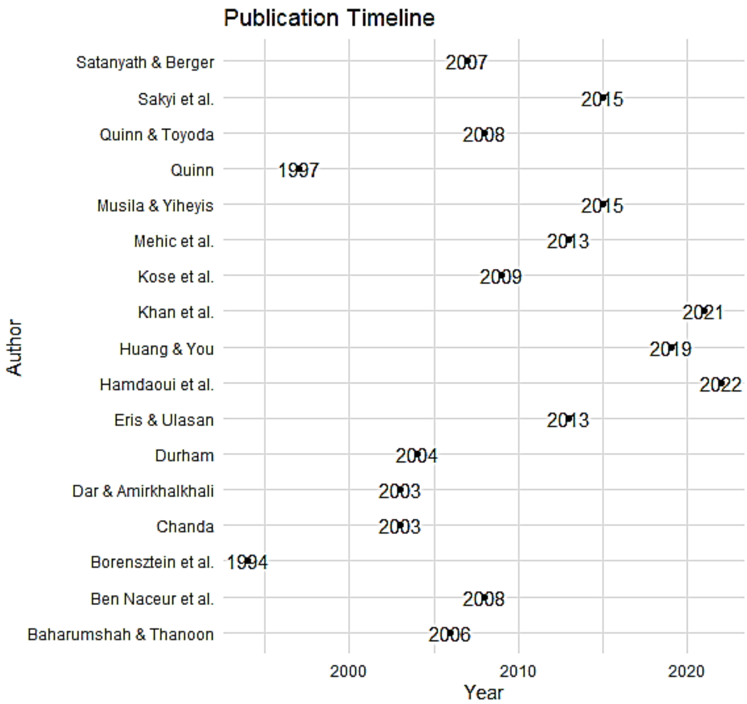


Figure 3 *Timeline Plot of Study Units in the Metadata Sample*

To the best of abilities, there has been efforts to include published studies as balanced as possible from the entire period, and the lack of studies for extended periods of years could come from a number of reasons, such as trends in academia. The mean year of the seventeen included studies is 2009, and the median is 2008, which are good points given the entire time period, and they either coincidentally or not happen to match up with the latest large worldwide financial crisis.

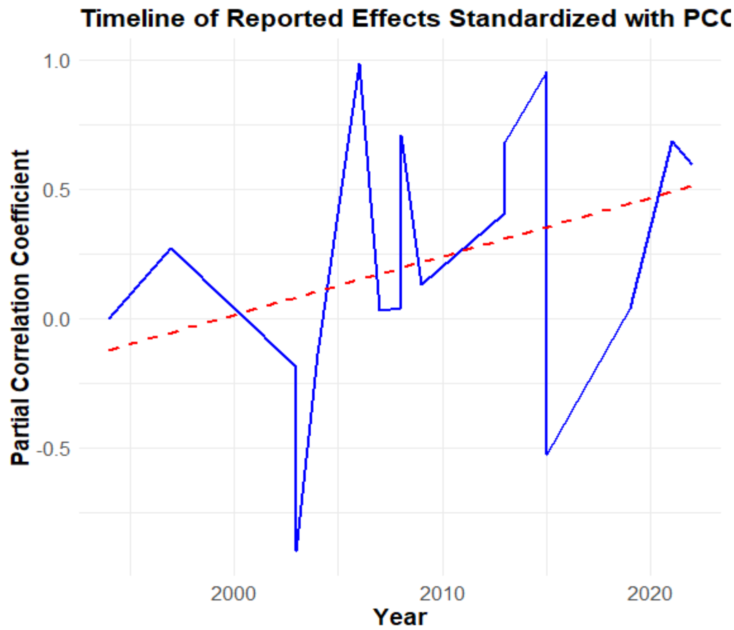


Figure 4 *Partial Correlation Coefficients Plotted Against Year of Reported Effect, Average PCC as Dotted Line*

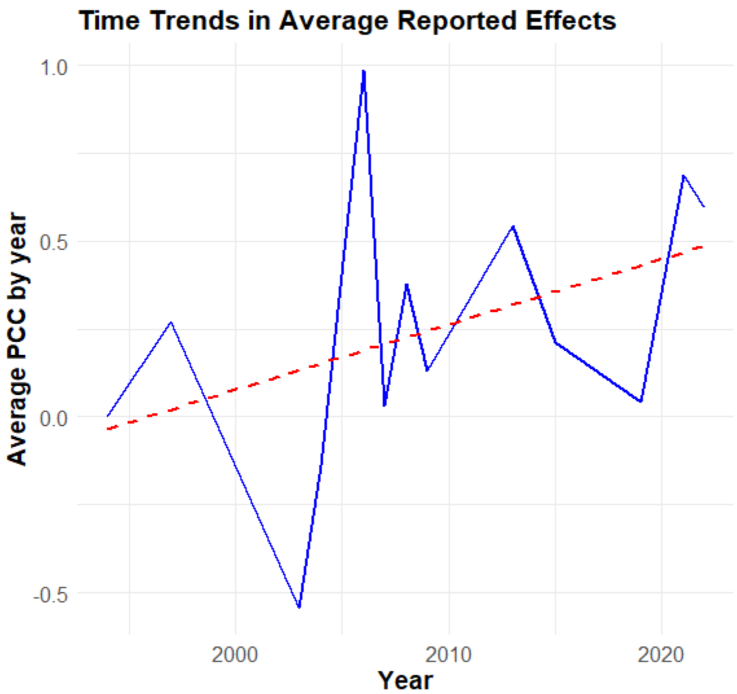


Figure 5 *Yearly Average Partial Correlation Coefficients Plotted Against Year of Reported Effects, Average PCC as Dotted Line*

When looking at figures 4 and 5 and their display of the reported effects of PCCs, there is a generally positive trend for reported effects over the entire period of the sample. Both plots start with a slightly negative reported effect for 1994, and the trend of reported effects rises upward for the entire period from there. In the first plot, we see clear negative peaks for reported effects for the years 2004 and 2015, and clear positive peaks for reported effects for the years 2006, 2008, 2015 and 2021. These peaks are also generally prevalent for the second graph in figure 5, where each years reported effect is averaged for the years that have two published studies and means that we can confidently say that the positive trend displayed in the first graph for economic growth is a just assessment of the general trend in the included studies.

5.2 Publication Bias

To assess the question of publication bias, which often comes to mind when conducting Meta-Regression Analysis (MRA), we use the tools of funnel plots and the Egger's test to do a rightful assessment of whether or not publication bias is present in the data we have, which have been explained as the assumption that significant and/or positive results are systematically overpublished by journals. By the funnel plots, we can assess whether the data is asymmetrical by the standard errors (precision of the estimate), and if we have an overweight of negative, positive, or neutrally reported effects by the scatter of the reported effects. The Egger's test on the other hand gives us quantifiable statistical results to prove the possible indications given by the graphical funnel plots. The test regresses the effect size estimates from each study against their precision, which gives us an intercept of a regression line that represents an estimate in the effect size due to publication bias given by:

$$SND = a + b * precision,$$

Generally, a p-value for the intercept of less than $p < 0.05$ suggests that publication bias is present due to a significant association between the standard errors and the estimates. For linear regressions without moderator variables, we can also output a b-value. The b-value indicates the estimated bias in the effect size as the standard error approaches zero, and therefore the potential asymmetry of high precision effect estimates.

	z-value	*p-value*	*b-value*	*CI*
Frequentist Fixed Effects Model (no moderators)	48.6493	**< 0.0001**	0.0306	0.0282 – 0.0331
Frequentist Mixed Effects Model (with moderators)	3.3214	**0.0009**	NA	NA

Table 3 *Results from the Egger's Test for Publication Bias for Frequentist Models*

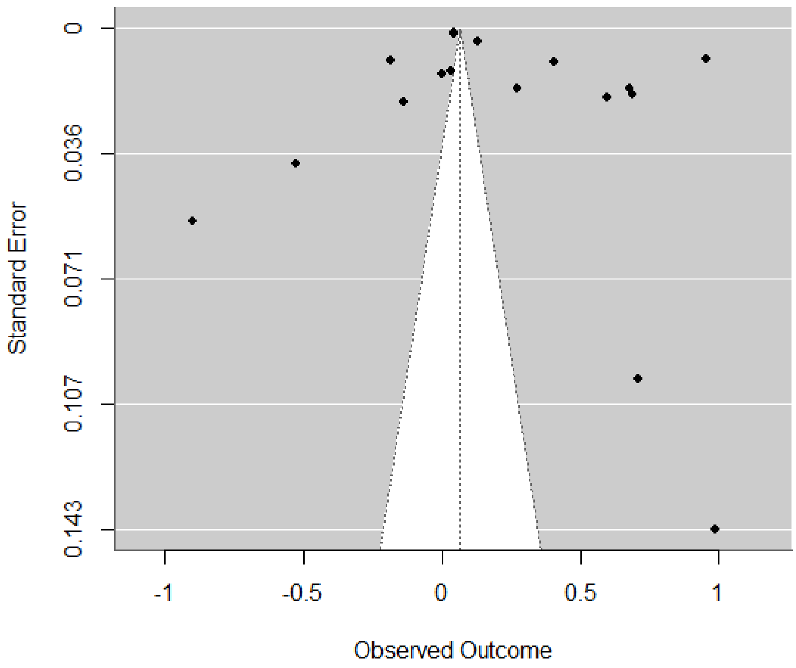


Figure 6 *Funnel Plot of Frequentist Fixed Effects Model without Moderators*

For the first funnel plot of figure 6, which is a funnel plot of the baseline frequentist meta-regression model of the PCC and standard error of the PCC with no moderator variables and fixed effects, there is clear asymmetry in the data inputs because high levels of standard errors are present. As for the spread of the observed outcomes, it is hard to establish clear indications of publication bias, as we have 8 negative observed outcomes in the model, and 9 positive observed outcomes. The asymmetry still indicates that this should be further assessed. The conducted Egger's test in table 3 of this baseline model gives us a p-value of < 0.0001, which concludes a strong assumption of publication bias. The b-value of the estimated bias in effect size is a positive 0.0306, and its confidence interval ranges from positive 0.0282 to 0.0331, meaning that we have a plausible publication bias with studies that report slightly positive effects on economic growth from capital flow and management techniques.

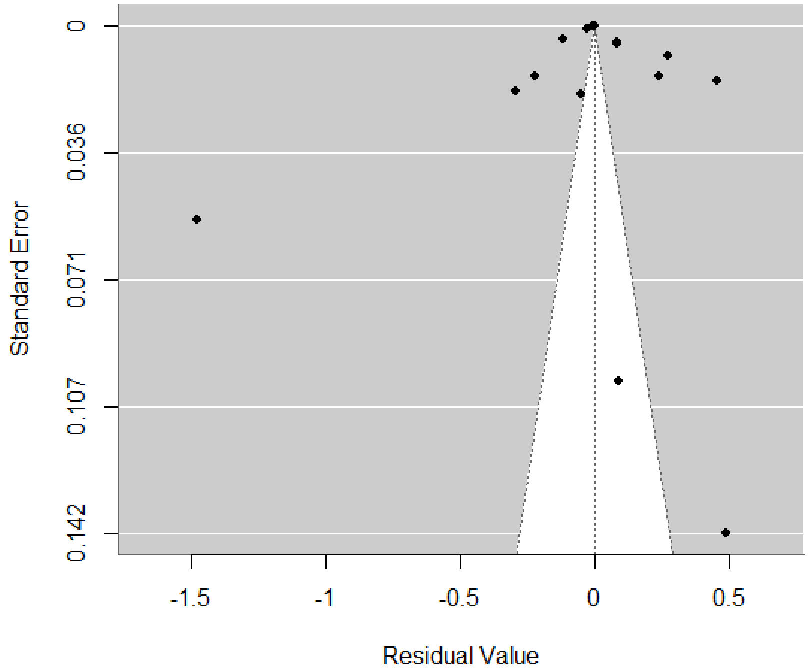


Figure 7 *Funnel Plot of Frequentist Mixed Effects Model with Moderators*

For the second funnel plot in figure 7, it is a funnel plot of a frequentist meta-regression model of the PCC and standard errors of PCCs with mixed effects and the addition of moderator variables of a dummy for time-series cross-sectional (TSCS) data, the publication year, a dummy for published article (as opposed to working paper), the sample size of the study, a dummy for reported effects that are statistically significant, a dummy for a political scientist writer (as opposed to economist), a dummy for the conceptualization "Capital Control" for capital flow management technique and the total time span of the data coverage in the study.

In this second funnel plot, the asymmetry is still present as in the first plot, with generally high levels of standard errors. The graphical indication of publication bias is still not very visible for this funnel plot either, but the conducted Egger's test of table 3 gave an output p-value of 0.0009, meaning we still have strong proof of indication towards positive publication bias on the reported effects of outcome on economic growth.

5.3 Frequentist Model Results

5.3.1 Forest Plot of Frequentist Fixed Effects Model without Moderators

To give a general idea on how each individual study has contributed in terms of weights (WLS) to the effect size data of the model, point estimates for each study, as well as calculated confidence intervals for each effect sizes, Figure 8 shows a forest plot of the reported observed outcomes and the overall observed outcome on economic growth given by the metadata per the frequentist fixed effects model. The square on each point estimate is a visual representation of the percentage of the total weight, shown besides each confidence interval, so the bigger the square, the bigger the weight. The weights are calculated by default as WLS within the meta-model by the input data we fit the model to from each study, such as the standard error of the PCC (the precision of the study). At the bottom of the forest plot, we have the calculated pooled effect (summary estimate) of the entire model along with its confidence interval.

By the forest plot in figure 8, the significantly largest weights to the pooled effect size, or mean estimate of the fixed effects model to economic growth is provided by the studies of Huang and You, and Quinn & Toyoda. These two also provide fairly low estimates on the effects on economic growth compared to some other studies, such as Ben Naceur et al. and Khan et al., and gives some explanation to why we have a pooled effect size that is positive, but not as high as we might expect given the strong positive trend given by our timelines of reported effects.

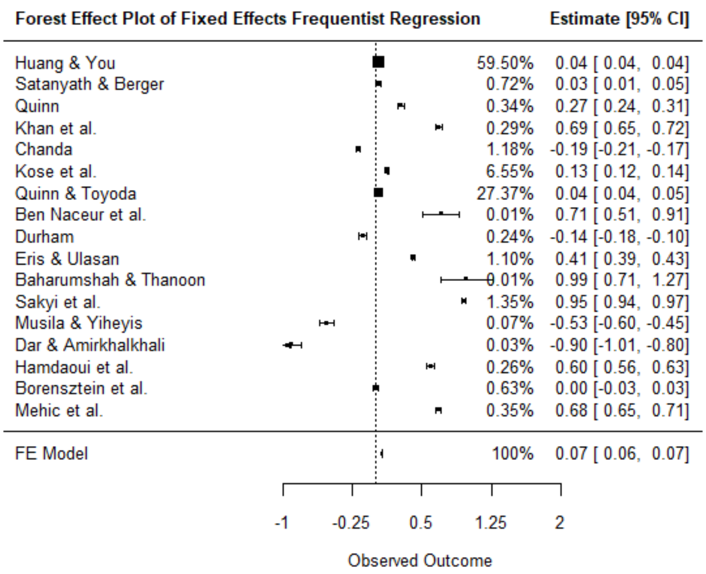


Figure 8 *Forest Plot of Frequentist Fixed Effects Model*

The pooled effect size (summary estimate) on economic growth of the frequentist fixed effects model is calculated to a positive effect of 0.07 on our standardized PPC measure with a confidence interval on the 95% estimate calculated to a range from positive 0.06 to 0.07, it is therefore a very precise measure of the overall effect given the weights and indicates a general trend of positively reported effects on economic growth. Now, the forest plot does not give us information on the direction or size of the effects of the moderator variables in the models, but it gives us valuable information on how the studies give "drive" to the model in its calculations, and thus which studies that provide to the bias in our funnel plots and Egger's tests. It is also obvious and important to note that in this model, most of the studies that report negative associations between capital flow management and economic growth are given lower weights than those who report positive effects, such as Musila & Yiheyis or Dar & Amarkhalkhali. The two studies that are given the highest weights are also two of the studies that are closest to the reference line of no effect. In other words, these studies do not drive a bias to either a positive or negative effect, and therefore they do not create any clear implications for further analysis.

5.3.2 Estimates Summary Table of Frequentist Models

In table 4, there is provided a regression estimates summary table of the frequentist fixed effects model and mixed effects model with moderators that have been previously discussed by the funnel plots and the forest plot. On the right side of the estimates table, we can see the same estimates and confidence intervals to each study as we did in the forest plot, but also the p-values relative to each study. The p-values depict if there is a significant effect between the study and the overall reported effect. Only one study is thought to have no statistically significant effect on the overall estimate, which is study number 16 in the list, Borensztein et al., the rest of the studies are significant on p-values on the 99.9% level ($p < 0.001$) and one study, Satanyath and Berger is statistically significant on the 95% level ($p < 0.05$). This means that there is a strong statistical connection between our reported effects and each study, which also is expected in an MRA-model where it is thought implicitly that all or most of the studies are so relatively related in their research questions that they affect the overall reported effect. We get no R^2-value for a linear model without moderators, so the study estimates table for the frequentist fixed effects model with no moderators give us no indication to try explaining the variance in the reported effects on economic growth by these studies. This, however, is provided by the frequentist mixed effects model to the left of the table, which has moderator variables present in each study represented for the overall effect.

For the left side of the table, we see no changes in levels of statistical significance to each study, which is good, because it means that the moderator variables provide proof to an already strong model and does not take away from the variance caused by each study individually. The moderators that are included are "DataTSCS", which is a dummy variable for time-series cross-sectional data, also known as panel data. Most of the studies have such data as basis for their analysis, and this variable therefore gives us insight in how this type of data affects the overall reported effect of studies as opposed to just time-series data, which only a few of the studies use. The next variable included is the publication year of each study, only described as "Year" in the table. As mentioned in the data-section of the thesis, both working papers and published articles are included as data, "TypeArticle" is therefore a dummy variable for the published articles. "n" represents the sample size of each original study, and "Significant" represents a dummy for if the original studies presented statistically significant results of their reported effects or not. "Pol_Sci" is a dummy for articles written by political scientists as opposed to economists, and "Capital_Control" is a dummy which represents Capital Control as the main conceptualization of capital flow management technique or policy. The last moderator, "time_span_years" is a numerical value for the total amount of years each study has data coverage for.

All moderator variables are statistically significant on the 99.9% level in affecting the reported effects, which means that they capture well the statistical variance in the model and how between-study characteristics affect reported outcomes. This is further captured by the R^2 of the model, which is not adjusted, as the data inputs to the model are standardized beforehand. We get an R^2 of 0.678, which means that our model and moderators capture a total of 67.8% of the variance in the reported effects of the studies, a reasonably high number relative to the amount of moderator variables that are included in the model.

Looking at the moderator variables in the table, we have some interesting results. The first moderator variable in the table, which represents type of data as TSCS, has a statistically significant positive effect of 1.26. This means that studies that are utilizing cross-sectional data along with time-series data, in general reports effects 1.26 points higher on the PCC-scale from negative 1 to 1 than studies that only utilize time-series data.

The second moderator in the model, the publication year of the studies, has a statistically significant effect on the reported effect, which is slightly positive at a value of 0.001. This indicates that studies published sooner in the publication range from 1994-2022 have a tendency to report effects 0.001 points higher than the previous year. In general, however, this tells us that earlier studies in general published more negative effects than later years.

Further on, TypeArticle, which as mentioned represents published articles as opposed to working papers, is statistically significant, and show us according to the model that finished articles which are published in academic journals in general report effects 0.58 points higher than working papers, which are the two types of publications we have as data for the thesis. Going back to the question of publication bias, which the funnel plots and Egger's tests gave strong indications were present for positively reported effects, is also backed up by this finding. If working papers do not establish strong enough positive effects, they might end up not being published at all, and thus stay as working papers for their entire lifespan.

	Frequentist (FE) with and without Moderator Variables					
Study Number in List and Moderators	*Estimates*	*Conf. Int (95%)*	*P-Value*	*Estimates*	*Conf. Int (95%)*	*P-Value*
Study 1	0.04 ***	0.04 – 0.04	**<0.001**	0.04 ***	0.04 – 0.04	**<0.001**
Study 2	0.03 *	0.01 – 0.05	**0.011**	0.03 *	0.01 – 0.05	**0.011**
Study 3	0.27 ***	0.24 – 0.31	**<0.001**	0.27 ***	0.24 – 0.31	**<0.001**
Study 4	0.69 ***	0.65 – 0.72	**<0.001**	0.69 ***	0.65 – 0.72	**<0.001**
Study 5	-0.19 ***	-0.21 – -0.17	**<0.001**	-0.19 ***	-0.21 – -0.17	**<0.001**
Study 6	0.13 ***	0.12 – 0.14	**<0.001**	0.13 ***	0.12 – 0.14	**<0.001**
Study 7	0.04 ***	0.04 – 0.05	**<0.001**	0.04 ***	0.04 – 0.05	**<0.001**
Study 8	0.71 ***	0.51 – 0.91	**<0.001**	0.71 ***	0.51 – 0.91	**<0.001**
Study 9	-0.14 ***	-0.18 – -0.10	**<0.001**	-0.14 ***	-0.18 – -0.10	**<0.001**
Study 10	0.41 ***	0.39 – 0.43	**<0.001**	0.41 ***	0.39 – 0.43	**<0.001**
Study 11	0.99 ***	0.71 – 1.27	**<0.001**	0.99 ***	0.71 – 1.27	**<0.001**
Study 12	0.95 ***	0.94 – 0.97	**<0.001**	0.95 ***	0.94 – 0.97	**<0.001**
Study 13	-0.53 ***	-0.60 – -0.45	**<0.001**	-0.53 ***	-0.60 – -0.45	**<0.001**
Study 14	-0.90 ***	-1.01 – -0.80	**<0.001**	-0.90 ***	-1.01 – -0.80	**<0.001**
Study 15	0.60 ***	0.56 – 0.63	**<0.001**	0.60 ***	0.56 – 0.63	**<0.001**
Study 16	0.00	-0.03 – 0.03	0.999	0.00	-0.03 – 0.03	0.999
Study 17	0.68 ***	0.65 – 0.71	**<0.001**	0.68 ***	0.65 – 0.71	**<0.001**
Overall	-30.20 ***	-31.97 – -28.43	**<0.001**	0.07 ***	0.06 – 0.07	**<0.001**
DataTSCS	1.26 ***	1.18 – 1.33	**<0.001**			
Year	0.01 ***	0.01 – 0.01	**<0.001**			
TypeArticle	0.58 ***	0.57 – 0.60	**<0.001**			
n	-0.00 ***	-0.00 – -0.00	**<0.001**			
Significant	0.54 ***	0.52 – 0.56	**<0.001**			
Pol_Sci	0.45 ***	0.41 – 0.49	**<0.001**			
Capital_Control	-0.50 ***	-0.53 – -0.48	**<0.001**			
time_span_years	0.01 ***	0.01 – 0.01	**<0.001**			
Observations	17			17		
R^2	0.678			NA		

* *p<0.05* ** *p<0.01* *** *p<0.001*

***Table 4** Estimates Summary Table of Frequentist Models. N = 17, p-values indicated by stars next to estimates.*

For sample size, we see that there is a statistically significant effect, but the effect is 0, meaning that according to the model, the sample size of the original study does not really relate to if the study reports positive or negative effects on the outcome of economic growth. This is in some ways an interesting finding, and in the name of science a good finding, as the original studies have a wide range of sample sizes, meaning that at least in these studies, the findings are somewhat robust no matter how big or small the initial sample.

For whether the studies present statistically significant results or not, the model suggests that studies who publish statistically significant results also report effects on economic growth that are 0.54 points higher than studies who conclude with statistically significant results. This, by nature, creates a concluding bias, because the studies that are statistically significant, and most people, both researchers and policy makers, seek to as evidence for claims when considering policy changes, in general report more positive effects on the outcome on economic growth.

The model also depicts how it affects the reported outcome of the original study if the writer is a political scientist as opposed to an economist. As we can see, political scientists in general report effects 0.45 points higher on the scale than economists. It is worth mentioning that political scientists only stand for one of the studies that were included as data, only because it was a real struggle to find political scientists that wrote on the topic. Still however, this study, Satanyath & Berger, utilizes the same method as the big part of the economists that have written the other studies, which are panel regressions. So, there is no methodological reason for political scientists not writing on the topic of liberal economic policy regarding capital flow and economic growth, and since the rest of the studies are written by economists, where also some report negative effects, that is the most reasonable explanation by the effect of this dummy variable.

In the studies, there are many conceptualizations of capital flow management policies, with a total of seven conceptualizations across seven studies. As a dummy here, the conceptualization of capital control is chosen as a dummy for being one of the most common across the studies. When the conceptualization of capital control is the writer’s chosen form of independent variable in an analysis, the reported effect in general is negative 0.50 points lower than all other conceptualizations. This tells us how the researchers conceptualize, and then also measure their flow management policy matters to the reported outcome effect, even when most of the conceptualizations are strongly related or even synonymous.

In the studies, there’s a wide range of data coverage from 40 years to sub 20 years. The model tells us that an increase in data-coverage by one year signifies a 0.01 increase in reported effect. Now, this might seem like a very little effect, but considering a great variance in time span across the data, an increase in data coverage by 15 years would result in a reported effect 0.15 higher than the overall estimate of 0.07 when the time span is zero, which is a large change considering the small sample and the range of PCC from negative 1 to 1. Thus, higher data coverage signifies a substantial increase in the reported effect on economic growth by a given policy or financial management technique.

Overall, we can thus say that the frequentist models provide us good indications on how the between-study characteristics included impact the reported effects on economic growth, and that the frequentist models to a great degree also capture this variance between study-characteristics. The significant, and strong negative overall effect in the mixed effects model indicates that the moderators included have a strong negative impact on reported outcomes of economic growth.

5.4 Frequentist Model Evaluations

As described in the methods-sections, several model tests have been conducted on the frequentist meta-regression models to ensure robust results and valid inferences.

QQ-Plots

QQ-Plots have been previously described as a test of the residuals against an expected normal distribution to reveal potential outliers and so that the values in the sample do not differ too much from the normal and contribute to potential sample bias (Marden 2004, 606). The plots are depicted by a straight (linear) regression line signifying a normal distribution of the theoretical quantiles, with individual plots for each sample quantile (like-positioned values) in the data sample. Depicted by figures 9 and 10, the sampled quantile distribution both for the fixed effects model and the mixed effects model are very close to the likely normal distribution of the data. No potential outliers are easily identified, and we can be confident that the sample does not induce bias due to any potential extreme values of units.

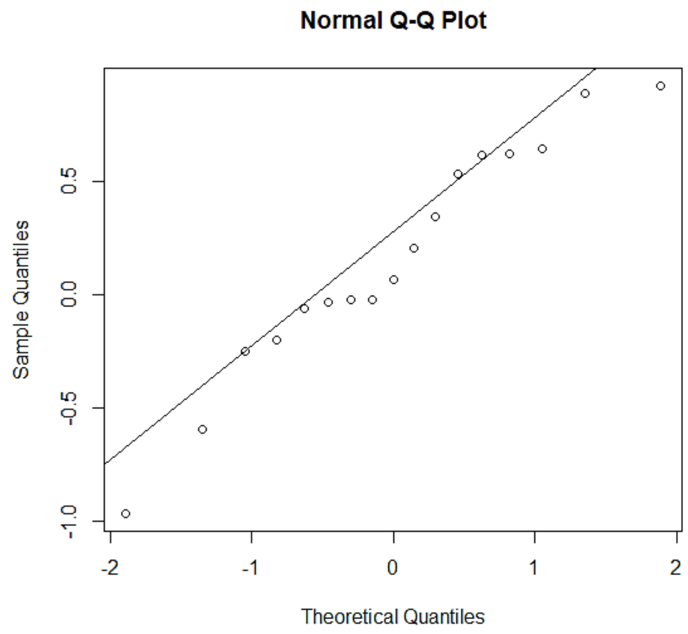


Figure 9 *QQ-Plot of Frequentist Fixed Effects Model*

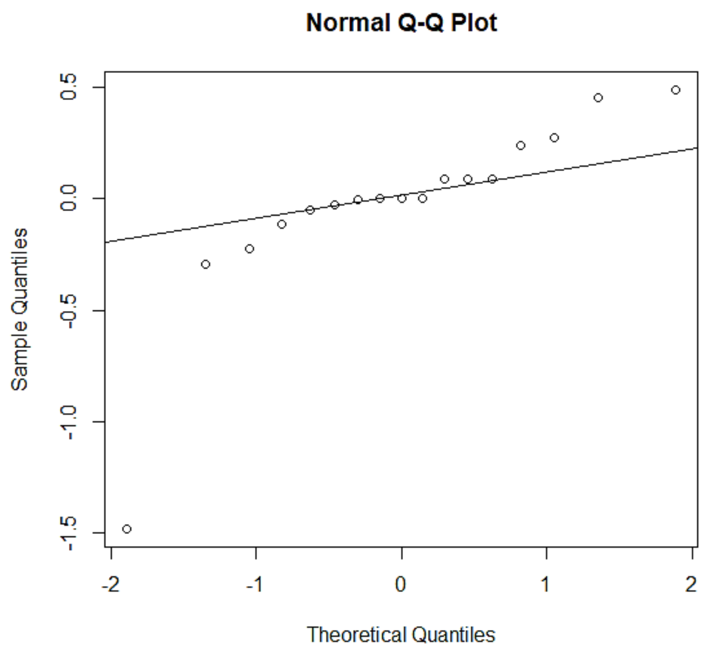


Figure 10 *QQ-Plot of Frequentist Mixed Effects Model*

Leverage Plots

Leverage plots have previously been defined as providing evidence of the distance between independent values of an observation from the independent values of other observations measured by Cook's distance (Cook 1977), here given by plots where the reference line is set at $2 * \frac{p}{n}$, a common denominator for “high leverage” given the data entries of the sample. The plots provide evidence of which ones of the units that cause larger changes in the parameter estimates of the regression models.

As seen in the plot of figure 11 of the frequentist fixed effects model, the studies 1 and 7 in the study index, referring to the studies by Satanyath & Berger and Kose et al. provide high leverage to the estimation of the parameters. Because the sample size already is limited to seventeen studies from the original twenty studies, the decision was made to not omit any studies based on leverage alone. Going further to figure 12 of the frequentist mixed effects model, more studies than not actually provide high leverage when moderators are added to the regression. The addition of moderators then “level out” the estimation of parameters in some ways, which indicates that the potential bias induced by high leverage studies decreases as the model gains in complexity. The tests are sufficient to keep all studies and not omit any units from the regressions.

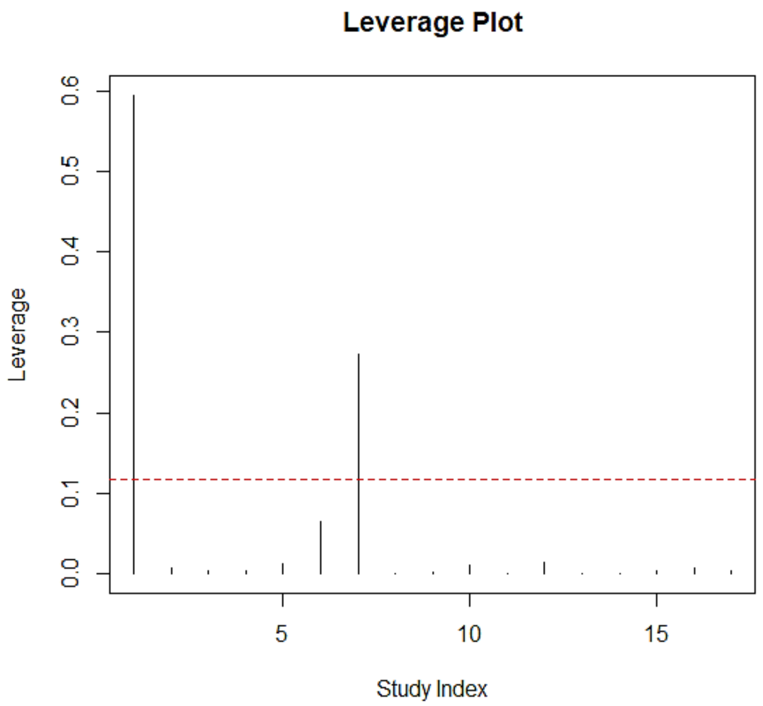


Figure 11 *Leverage Plot of Frequentist Fixed Effects Model*

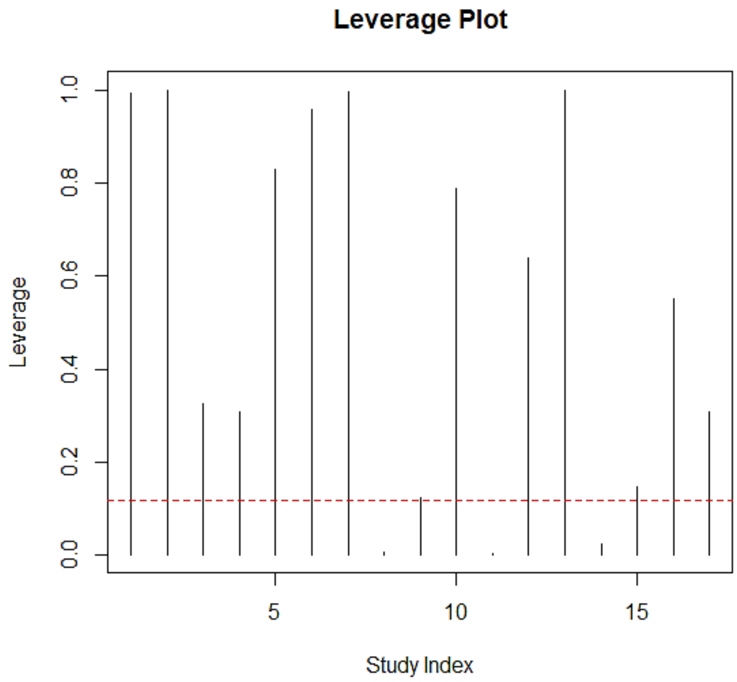


Figure 12 *Leverage Plot of Frequentist Mixed Effects Model*

Breusch-Pagan Tests

The Breusch-Pagan test, which helps to evaluate if the assumption of homoscedasticity in linear regressions are met by looking at the variance across all levels of the independent variables in the models, are visualized graphically by the plots in figures 13 and 14. For both the fixed effects and mixed effects frequentist models, we conclude that the assumptions of homoscedasticity in linear models are met, and that we have unbiased coefficients. In the frequentist model with fixed effects and no moderators, there's clear fanning out of the residual values, but not induced by an increase in the potential values as these are held constant, and thus not a direct connotation to induced heteroscedasticity, because that model only has one moderator, namely the standard error of the PCC. For the frequentist mixed effects model with moderators, there's a clear symmetrical pattern around the zero-value for residuals that does not rampantly fan out when the predictor values increase – thus, we can conclude with unbiased moderators.

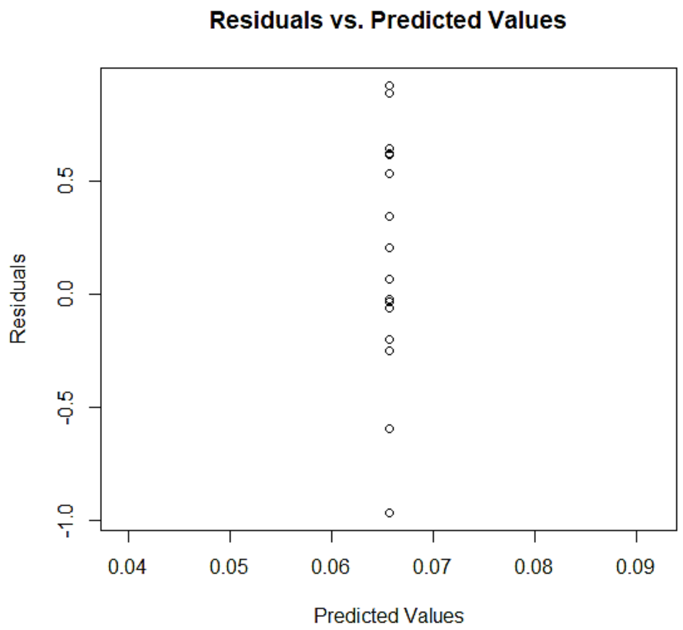


Figure 13 *Breusch-Pagan Test of Frequentist Fixed Effects Model*

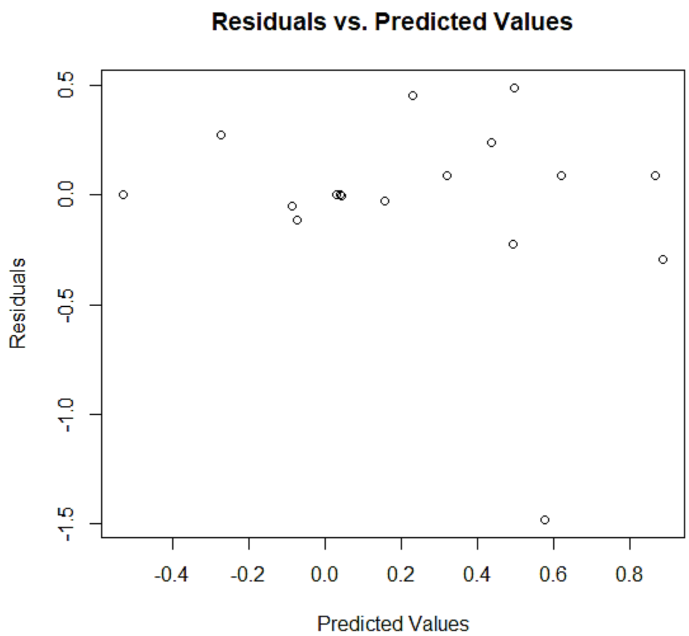


Figure 14 *Breusch-Pagan Test of Frequentist Mixed Effects Model*

Wald Test (statistics) of Coef. Index 2 in Frequentist Mixed Effects Model

The Wald Statistic has previously been explained as an extra measure for statistical investigation of the significance level of certain moderators in the regression estimates. As stated, values of the statistic above 1.96 are "high" and thus assume significance on the 95% level and helps to determine predictors of the parameters of the model across all units. For Wald statistics, it was chosen to test the second coefficient of the mixed effects model, shown in table 5, equivalent to the “DataTSCS”-dummy moderator variable. By the statistics, we can see that the estimate of this variable is on a clearly significant level with a statistic of 74.92585, we can therefore be confident that the inferences drawn from the estimates of this variable are valid no matter which other moderators we include or omit from the model.

	Wald-Statistic	***Degrees of Freedom***	***p-value***
Coef. Index 2 of Frequentist Mixed Effects Model	**74.92585**	8	5.103695e-10

Table 5 *Wald Test (statistics) of Coefficient Index 2 in the Frequentist Mixed Effects Model*

Likelihood Ratio Test (LRT)

In table 6 is a conducted LRT-test of the frequentist models to help evaluate the fit of the lesser complex fixed effects model, and the more complex mixed effects model with moderators. The degrees of freedom which were calculated were consistently at 5, indicating a fixed number of parameters across both the models. The Log-likelihood ranges from negative 8419 to negative 1307 and shows the variability in the model-fit. The consistent negative values suggests that the models vary in how well they fit the data. This indication is also verified by the chi-square statistic, with a consistent, large value of 14224 across the board, indicating a substantial difference in fit between the two models. These statistics are highly significant as per the far-right row of the table, and the indication of varying fit is also valid.

The p-values for the chi-statistics are consistently 0, indicating that the observed Chi-square statistics are highly valid observations. In conclusion, the LRT-test results indicate that there is a significant improvement in the fit of the full model (mixed effect) compared to the reduced model (fixed effects). The Chi-square statistic is consistently large, and the p-values are all 0, suggesting that the additional parameters in the full model contribute significantly to better model fit. This means that the simpler (reduced) model is not adequate, and the more complex (full) model should be preferred.

DF	LogLik	DF	Chi sq.	Pr (>Chi sq.)
Min.: 1	Min.: -8419	Min.: -8	Min.: 14224	Min.: 0
1st Qu.: 3	1st Qu.: -6641	1st Qu.: -8	1st Qu.: 14224	1st Qu.: 0
Median: 5	Median: -4863	Median: -8	Median: 14224	Median: 0
Mean: 5	Mean: -4863	Mean: -8	Mean: 14224	Mean: 0
3rd Qu.: 7	3rd Qu.: -3085	3rd Qu.: -8	3rd Qu.: 14224	3rd Qu.: 0
Max.: 9	Max.: -1307	Max.: -8	Max.: 14224	Max.: 0

Table 6 *LRT-test of Frequentist Mixed Effects Model*

Robustness Test with Alternative Specification

To further assess the robustness of the frequentist mixed effects model, an alternative specification to the model has been developed, and is provided in table 7. The alternative specification fit to the model was to only add the “Year” and “Capital_Control” variables as moderators and leave all other initial moderators of the mixed effects model out. This introduced some new and interesting findings. By leaving all other moderators except the publication year and dummy for capital control-conceptualization, the moderator for publication year lost its significance. This might be an indication that the publication year is mutually dependent on at least one other variable in order to be a significant factor in the reported outcomes on economic growth in research. The dummy variable for capital control as the conceptualization of the independent variable kept its significance level but had a drastic reduction in its estimated negative effect on the reported outcomes on economic growth. This variable is also dependent on other moderators, which is surprising when we have concluded with unbiased coefficients as per the conducted Breusch-Pagan tests. The alternative specification test suggests that the frequentist mixed effects model is sensitive to changes in the included moderators, and that the inferences we draw from it are less valid due to a lack of consistency and robustness. The significance loss is also present in the summary mean estimation of the model, signifying that other moderators affect the reported outcomes on economic growth more negatively than the two moderators of the alternative specification model.

Study Number in List and Moderators	Frequentist (FE) with Moderator Variables and Alternative Specifications Estimates	Conf. Int (95%)	P-Value	Estimates	Conf. Int (95%)	P-Value
Study 1	0.04 ***	0.04 – 0.04	**<0.001**	0.04 ***	0.04 – 0.04	**<0.001**
Study 2	0.03 *	0.01 – 0.05	**0.011**	0.03 *	0.01 – 0.05	**0.011**
Study 3	0.27 ***	0.24 – 0.31	**<0.001**	0.27 ***	0.24 – 0.31	**<0.001**
Study 4	0.69 ***	0.65 – 0.72	**<0.001**	0.69 ***	0.65 – 0.72	**<0.001**
Study 5	-0.19 ***	-0.21 – -0.17	**<0.001**	-0.19 ***	-0.21 – -0.17	**<0.001**
Study 6	0.13 ***	0.12 – 0.14	**<0.001**	0.13 ***	0.12 – 0.14	**<0.001**
Study 7	0.04 ***	0.04 – 0.05	**<0.001**	0.04 ***	0.04 – 0.05	**<0.001**
Study 8	0.71 ***	0.51 – 0.91	**<0.001**	0.71 ***	0.51 – 0.91	**<0.001**
Study 9	-0.14 ***	-0.18 – -0.10	**<0.001**	-0.14 ***	-0.18 – -0.10	**<0.001**
Study 10	0.41 ***	0.39 – 0.43	**<0.001**	0.41 ***	0.39 – 0.43	**<0.001**
Study 11	0.99 ***	0.71 – 1.27	**<0.001**	0.99 ***	0.71 – 1.27	**<0.001**
Study 12	0.95 ***	0.94 – 0.97	**<0.001**	0.95 ***	0.94 – 0.97	**<0.001**
Study 13	-0.53 ***	-0.60 – -0.45	**<0.001**	-0.53 ***	-0.60 – -0.45	**<0.001**
Study 14	-0.90 ***	-1.01 – -0.80	**<0.001**	-0.90 ***	-1.01 – -0.80	**<0.001**
Study 15	0.60 ***	0.56 – 0.63	**<0.001**	0.60 ***	0.56 – 0.63	**<0.001**
Study 16	0.00	-0.03 – 0.03	0.999	0.00	-0.03 – 0.03	0.999
Study 17	0.68 ***	0.65 – 0.71	**<0.001**	0.68 ***	0.65 – 0.71	**<0.001**
Overall	-30.20 ***	-31.97 – -28.43	**<0.001**	-0.01	-0.74 – 0.72	0.974
DataTSCS	1.26 ***	1.18 – 1.33	**<0.001**			
Year	0.01 ***	0.01 – 0.01	**<0.001**	0.00	-0.00 – 0.00	0.832
TypeArticle	0.58 ***	0.57 – 0.60	**<0.001**			
n	-0.00 ***	-0.00 – -0.00	**<0.001**			
Significant	0.54 ***	0.52 – 0.56	**<0.001**			
Pol_Sci	0.45 ***	0.41 – 0.49	**<0.001**			
Capital_Control	-0.50 ***	-0.53 – -0.48	**<0.001**	-0.07 ***	-0.08 – -0.05	**<0.001**
time_span_years	0.01 ***	0.01 – 0.01	**<0.001**			
Observations	17			17		
R^2	0.678			0.000		

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

Table 7 *Robustness Test, Alternative Specification of the Frequentist Mixed Effects Model (first) vs. Alternative Specification Year + Capital Control (second)*

5.5 Bayesian Model Results

As with the frequentist models, there are also provided two different Bayesian models, one without (baseline estimation), and one with moderator variables, meaning that the analysis has a total of four models for comparison in the discussion of the thesis. The Bayesian models are both random effects models, which in Bayesian regression models are the equivalent of a hierarchical model, or "tree-like structure" of each group of the data, which in this case is the authors of each study. This is also known as multilevel modeling (MLM), where we have individual estimates of all group levels (authors), and all population levels (moderators). Even though they are random effects models, the population-level effects consider fixed effects by referring to the average effect predictor variables have on the outcome variable of reported effects on economic growth. Since the first model does not include any moderators or "predictors" outside the studies themselves as groups, these fixed effects cannot be considered until we assess the Bayesian model with the same moderators included as in the frequentist mixed effects model with moderators.

5.5.1 Results of Baseline Bayesian Random Effects Model

For the Bayesian model with no moderators shown in table 8, it converges, which means that the interpretations and assessments of the models can continue, because the R-hat values for both group-level and population level effects that are equal to R-hat = 1. In Bayesian regression, R-hat values, *also known as the Gelman-Rubin statistic*, close to 1 (e.g., less than 1.1) signifies convergence. Convergence signifies reliable estimates, in that we have enough iterations of our data so that the chains have converged to the same distribution – meaning an adequate sample. When we have reliable estimates in our Bayesian models, the inferences we can draw from them are strong. All values lower than 1.1 indicate convergence, but the closer to or equal to 1 this value is, the stronger the convergence. For this model, the sampling has been computed in draws of four chains of iterations. The R-hat indicates that all these four chains have converged to the same sample distribution even when initialized at different points in time of the modelling iterations of the data.

	Estimate	***Est. Error***	***lower-95% CI***	***upper-95% CI***	***R-hat Value***	***Bulk ESS***	***Tail ESS***
Group-Level Effects (Intercept)	**0.56**	0.12	0.38	0.83	**1.00**	**827**	**1179**
Population-Level Effects (Intercept)	**0.22**	0.13	-0.04	0.48	**1.00**	**760**	**925**

Table 8 *Summary Estimates of Baseline Bayesian Random Effects Model. N = 17, draws in 4 chains, each with iterations = 4000, warmup = 2000. Total post-warmup draws = 8000*

For the baseline Bayesian regression estimates of the posterior distribution shown in table 8, we see clear convergence in both the group-level and population-level effects of the model with R-hat values equal to 1. The Effective Sample Size (ESS), meaning the relative sample size of the model to the initial sampling, has low sample sizes considering the initial sampling has 8000 draws, both in the tails and in the bulk of the sample. The ESS is still large enough from which to draw inferences, and much larger than the sample size of seventeen in the frequentist models. In the population-level effects, which in this case is the standard error to the PCC as the only coefficient, the precision of the studies provides plausible positive effects on the reported outcomes on economic growth.

As we can see in table 9, all groups – meaning authors – in our model have their own estimated effect in the posterior distribution that lies between two estimated intervals along with the estimated error to each group estimate. This estimated effect is interpreted as the average effect for each group, and we also have a positive mean estimate of the reported effect of the group equal to positive 0.56 with a confidence interval ranging from positive 0.38 to 0.83 based on the individual estimates to each author. According to the Bayesian random effects model without moderators, we should then expect a plausible value of an average reported positive effect of 0.56 on the relationship between capital flow and management techniques and economic growth, meaning a quite strong positive effect when we have a PCC range of standardized measures from negative 1 to 1.

Group-Level Intercepts by Authors	***Estimate***	***Est. Error***	***Q2.5***	***Q97.5***
Baharumshah & Thanoon	**0.71511540**	0.1864548	0.34843342	1.07384155
Ben Naceur et al.	**0.47569692**	0.1637703	0.15753141	0.79753970
Borensztein et al.	**-0.21657168**	0.1350937	-0.48654631	0.04144068
Chanda	**-0.40323930**	0.1360652	-0.67253365	-0.83581963
Dar & Amirkhalkhali	**-1.10761584**	0.1455853	-1.40538002	-0.883581963
Durham	**-0.35390870**	0.1360652	-0.62925751	-0.09185741
Eris & Ulasan	**0.19147407**	0.1347568	-0.07735427	0.44966173
Hamdaoui et al.	**0.37839075**	0.1357202	0.10342827	0.63594254
Huang & You	**-0.17587111**	0.1345785	-0.44354663	0.08211692
Khan et al.	**0.46966143**	0.1357872	0.19669389	0.72906322
Kose et al.	**-0.08673019**	0.1345721	-0.35450051	0.17318602
Mehic et al.	**0.46156840**	0.1354113	0.19165545	0.72184758
Musila & Yiheyis	**-0.74171364**	0.1390219	-1.02587984	-0.47860140
Quinn	**0.05456161**	0.1353668	-0.21677958	0.31514987
Quinn & Toyoda	**-0.17516029**	0.1346506	-0.443150508	0.08273769
Sakyi et al.	**0.73707337**	0.1345612	0.46982896	0.99418063
Satanyath & Berger	**-0.18584695**	0.1352571	-0.45677406	0.07561630

Table 9 *Group Level Estimates of Baseline Bayesian Model.*

For the group level effects of the Bayesian regression with random effects and no moderators in table 9, the estimated reported effects vary to a great degree from group to group, which in turn, the moderators added later should help explain. Our lowest estimated reported effect is negative 1.1 by Dar & Amirkhalkhali with an uncertainty interval ranging from negative 1.40538 to negative 0.83581. As we already know by the standardized PCC, the reported effect must range from negative 1 to positive 1, so the estimated lowest reported effect represented by this study must come in the upper percentiles of the confidence interval in order to be within parameters. Given the estimated error of 0.14558 and these intervals, we can be pretty certain that the calculations are correct even though the mean estimate falls outside the range. The highest mean estimate of reported effects comes from Baharumshah & Thanoon with a positive estimate of 0.71511 within an uncertainty interval of positive 0.34843 to 1.07384. But what does this really tell us about the connection of the studies and the reported effects on economic growth? Well, in a scenario where all these studies have been stripped from between-study characteristics such as sample sizes, the Bayesian regression estimates find it plausible that these studies would report standardized effect estimates of close to negative 1 for Dar & Amirkhalkhali on the impact of liberal economic policy on economic growth, while the authors Baharumshah & Thanoon most likely would report a standardized effect size measure close to positive 0.7 for the effect of a liberal economic policy and economic growth. These two different groups of authors are by default biased by our calculations, in that one group most likely would report high negative effects, and the other group most likely would report high positive effects of such policies.

For the Bayesian model with moderator variables, we can also consider the population-level effects, which represent the average fixed effects of the moderator variables across all groups in the data. As with the group-level effects of the first model, we also get R-hat values for each single population-level. As we can see by this model as well, we have R-hat values for both the group-level and all population-level effects that are equal to 1, meaning that our parameters and thus model have converged to the same distribution across chains of iterations. According to these statistics, the reliability of the model is very high, and the inferences we can draw from it are strong.

There are plots of the population-level and group-level effects by the standardized mean difference (SMD) and Tau (*t*) for the baseline Bayesian regression model in figures 15 and 16. The Tau-value assesses the between-study variance in the sample, meaning the Group Level-Effects estimates and its uncertainty, while the estimated population-level effects are shown by the plot of the standardized mean difference of positive 0.22, where Tau is calculated to positive 0.56. Both these plots give visual representations of the calculated estimates in the Bayesian regression in table 8, along with the colored cones representing the estimated confidence intervals.

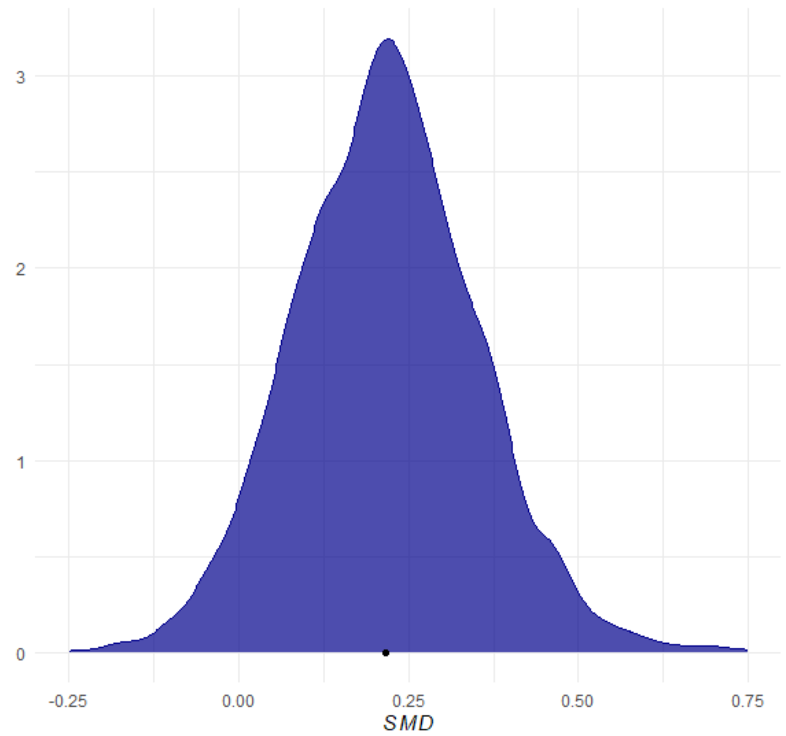


Figure 15 *Plot of Population Level Effects of Baseline Bayesian Model (SMD)*

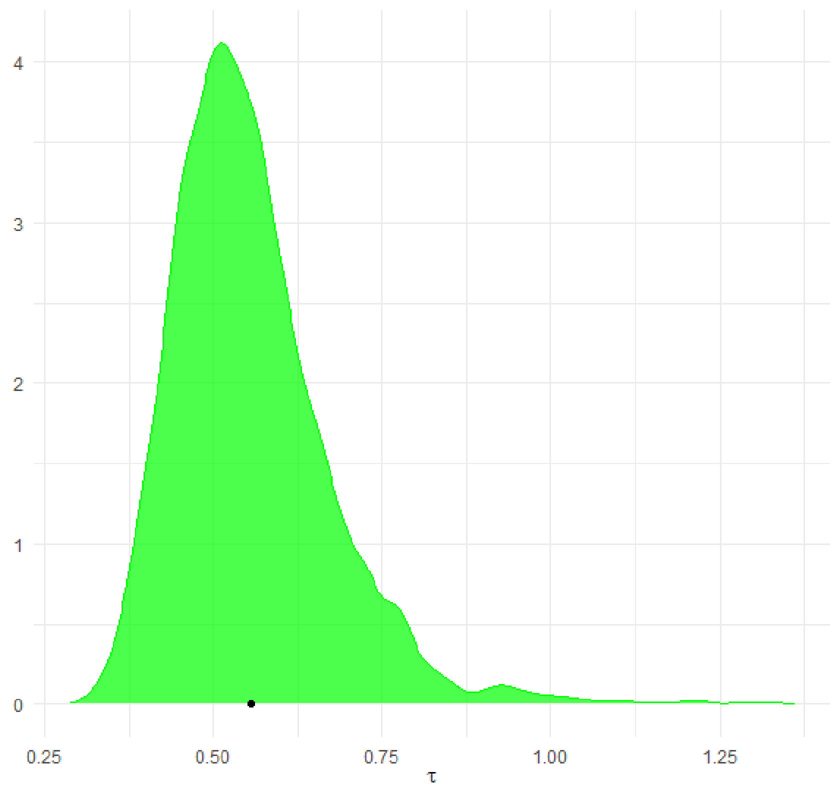


Figure 16 *Plot of Group Level Effects of Baseline Bayesian Model* (*tau*)

The forest plot displayed by figure 17 presents a summary of the standardized mean difference to all studies – an estimated effect size – by the baseline Bayesian random effects model along with 95% confidence intervals to each estimate. The plot shows varying estimates of reported outcomes on economic growth across all the study units with an estimated standardized mean difference of 0.22. What this means, is that given the posterior distribution of the estimation, we should expect a reported positive effect size on the PCC-measure of 0.22 on economic growth, meaning we have an overall positive effect between capital flow and management techniques and economic growth. Based on the Bayesian analysis, there is calculated a probability of the pooled effect being < 0.30, which gave a 74.4875% probability that the pooled effect size is less than 0.30. This provides insight into the uncertainty surrounding the estimate of the pooled effect size, indicating the degree of belief that the true value of the effect size falls below 0.30.

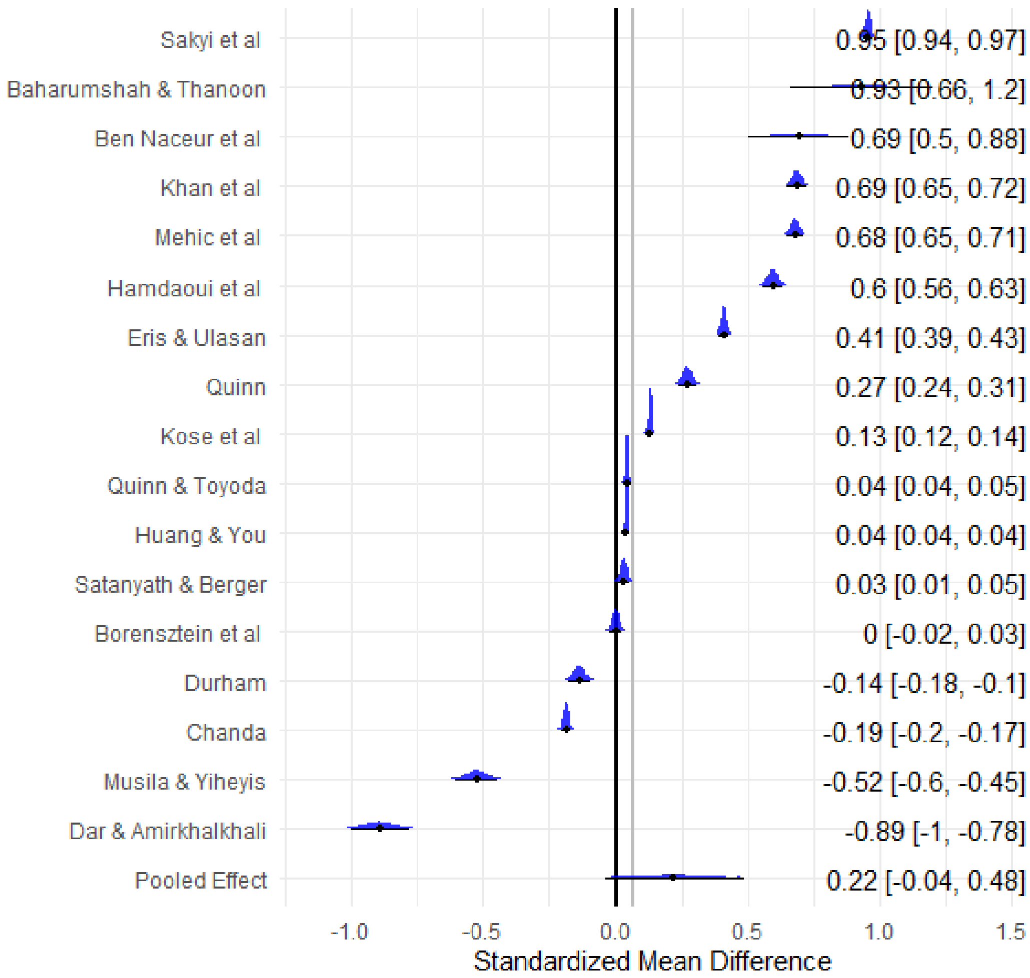


***Figure 17** Forest Plot of Pooled Effect of the Standardized Mean Difference, Baseline Bayesian Model, Probability Pooled Effect < 0.30 = 0.744875*

5.5.2 Results of Bayesian Random Effects Model with moderators

	Estimate	Est. Error	Lower-95% CI	Upper-95% CI	R-hat value	Bulk ESS	Tail ESS
Group-Level Effects (Intercept)	**0.62**	0.18	0.37	1.08	1.00	2689	3572
Population-Level Effects (Intercept)							
Intercept	**-64.01**	47.48	-158.84	26.46	1.00	5420	4817
Data TSCS (dummy)	**1.19**	0.71	-0.21	2.57	1.00	7162	5080
Year	**0.03**	0.02	-0.01	0.08	1.00	5437	4757
Type Article (dummy)	**0.18**	0.60	-1.04	1.38	1.00	6139	4973
N (sample size)	**0.00**	0.00	-0.00	0.00	1.00	6866	5440
Significant (dummy)	**0.45**	0.46	-0.45	1.38	1.00	4672	4681
Political Scientist (dummy)	**0.39**	0.94	-1.54	2.26	1.00	5531	4933
Capital Control (dummy)	**-0.31**	0.54	-1.39	0.76	1.00	5322	5217
Time Span of Data	**-0.00**	0.02	-0.04	0.04	1.00	5808	5262

Table 10 *Summary Estimates of Bayesian Random Effects Model with Moderators. N = 17, draws in 4 chains, each with iterations = 4000, warmup = 2000. Total post-warmup draws = 8000*

As for the frequentist fixed effect model with moderators, the same moderator variables have been fit to the Bayesian random effects model with moderators to ensure that the resulting inferences and comparisons that can be conducted across the different models are consistent in their contents. According to this model shown by table 10, time-series cross-sectional data has an impacted positive effect estimate of economic growth by 1.19, meaning that the plausible effect of utilizing these types of data as opposed to just time-series data will have a positive impact on the reported effect on economic growth. Further on, a positive estimate of the publication year of 0.03 suggests that the more recent a study is published, the more positive the reported effect of the study will be. An article will plausibly report effect sizes on economic growth that are 0.18 points higher as opposed to a working paper. As with the frequentist model, the sample size of the initial study seems to have no real impact on the reported effect size, which is a strong indicator with an estimated error of 0.00. It also helps strengthen the inferences we can draw from it, that it is that consistent in suggesting no to very little impact across different regression-type models. Further strengthening the assumptions that we have drawn from our assessment of publication bias earlier in the analysis; the Bayesian model also suggests a positive impact on the reported effect if the reported effect sizes also are reported as statistically significant findings. When utilizing a reference point of 0 on the negative 1 to 1 scale that signifies no effect, the plausible effect of a political scientist writer is a positive impact on the reported effect size of 0.39. Now, as in the frequentist model, the conceptualization of capital control as opposed to other conceptualizations of liberal economic policy in literature, suggests that authors utilizing that specific conceptualization most likely would report more negative effect sizes than authors who utilize other conceptualizations. In the instance of the Bayesian model, we have an expected estimate of negative 0.31. The time span of the data coverage, as the sample size, seems to have no or a very small negative plausible effect on the reported effect on economic growth of a study.

To assess the practical significance of the parameter estimates, there's also included an assessment of the Region of Practical Equivalence (ROPE)-statistics to all the population-level parameters shown in table 11. As previously defined in the methods-section, these statistics help to determine whether the posterior distributions of each parameter fall within a predefined range practically equivalent to zero. If the values fall within our predefined ROPE, the inferences we can draw from them are small to none, as they are basically indifferent to the null or reference value we have – high ROPE-probabilities suggest that the estimated effect in our model is not practically meaningful, and that we can consider the inferences drawn from these parameters negligible. As a practical example, it is similar to significance testing in frequentist linear regression, but instead of looking at p-values, we're considering the percentage of a posterior distribution within the ROPE as an alternative to traditional hypothesis testing. As baselines, we are using the percentages of 95% as a high percentage where we have insufficient evidence to draw strong conclusions, 80%-95% as a moderate percentage where we can draw conclusions if the context is right, and below 80% as a low percentage where the estimated effect is plausible and relevant for practical assessments of the effects. The effective sample sizes related to the model parameters in table 10 are also much higher compared to the baseline Bayesian estimation, meaning that the inferences we can draw from this estimation are stronger compared to the initial model, as we have "more" data to evaluate on a larger population.

For the Bayesian random effects model, all moderator variables except the publication year, sample size and time span of data coverage fall well outside the 80% range. This means that the conclusions that are drawn from these parameters most likely have strong proof of truth in real life situations. As for the three mentioned parameters, they all fall within 100% of the ROPE. This does not mean that we should ultimately look away from these moderators for explanations, but try to determine by our data why these parameters are bad at explaining variance in reported outcomes in the Bayesian model. First, the trends that have been observed show a real development in the included data that the reported effect sizes on economic growth have increased over the years, which it is very unlikely that is just a random development. The suggestion is therefore that there is too little data units in this analysis to take the publication years into consideration, as there is a pretty long time period that is explained with not too many units of published articles and working papers. Second, for sample size and data coverage, the suggestion here is also that the sample size of this analysis is too small to consider these parameters. With more variance within the input data, the Bayesian model would most likely have enough sample data to also calculate the real significance of these parameters.

Parameter	*Median*	*95% CI*	*pd*	*% in ROPE*	*R-hat*	*Bulk-ESS*
(Intercept)	**-63.98**	-158.84, 26.46	92.54%	0.08%	**1.001**	**5338**
Data TSCS (dummy)	**1.20**	-0.21, 2.57	95.58%	2.76%	**1.000**	**7039**
Year	**0.03**	-0.01, 0.08	91.95%	100%	**1.001**	**5354**
Type Article (dummy)	**0.18**	-1.04, 1.38	63.01%	14.29%	**1.001**	**5927**
N (sample size)	**1.06e-04**	-0.00, 0.00	52.26%	100%	**1.001**	**6712**
Significant (dummy)	**0.45**	-0.45, 1.38	84.90%	10.80%	**1.002**	**4646**
Political Scientist (dummy)	**0.39**	-1.54, 2.36	67.42%	8.93%	**1.000**	**5405**
Capital Control (dummy)	**-0.31**	-1.39, 0.79	73.76%	13.64%	**1.000**	**5229**
Time Span of Data	**-4.72e-04**	-0.04, 0.04	50.91%	100%	**1.000**	**5757**

Table 11 *Summary of Posterior Distributions in the Population Levels of Bayesian Random Effects Model with Moderators. All ROPE-intervals = [-0.10, 0.10]*

There's also a calculated Bayes R^2 for both Bayesian models as a measure of goodness of fit of the regression models as displayed by table 12. As with the frequentist linear regression models, it provides an estimate of the proportion of variance in the reported effect on economic growth by our units and moderator variables but calculated within the Bayesian framework of posterior distributions. The Bayes R^2 is therefore equal to 1 - $\frac{Posterior\ mean\ of\ residual\ variance}{Posterior\ variance\ of\ the\ outcome\ variable}$, ranging in values from 0 to 1, where 0 indicates no explanatory power by the predictors in our model, and a value of 1 indicates perfectly explained variance by the predictors.

	Estimate	***Est. Error***	***Q2.5***	***Q97.5***
Bayes R^2 of Baseline Bayesian Random Effects Model	**0.9910524**	0.008074086	0.9694002	0.9988901
Bayes R^2 of Bayesian Random Effects Model with Moderators	**0.9914302**	0.00767219	0.9706461	0.9989491

Table 12 *Summary of Bayes R^2 Estimates for Bayesian Models*

For the first model with no moderator variables, there is a calculated Bayes R^2 of approximately 0.99105 with uncertainty levels Q2.5 = 0.96940 and Q97.5 = 0.99889, and with the added moderator variables in the second model, there is a Bayes R^2-output of 0.99153 with Q2.5 = 0.97064, and Q97.5 = 0.99894, which are very high estimates of explained variance. As for the uncertainty, both models have low ranges of uncertainty. Since there is an increase in the Bayes R^2 after the addition of moderator variables, we can confirm that these variables add to the explained variance, and that they do not deduct any explanation from the model. Both values are still so close to 1 that a lot of the explained variance comes from the groups or authors themselves. As in the context of the research question for explaining differences in reported effects on economic growth by studies where capital flow management techniques are independent variables, the nature of data is standardized and should thus capture the relevant aspects of the data needed to utilize the Bayes R^2 as a measure for goodness of fit of the models, and we can confidently say that both Bayesian models have very little uncertainty related to them. The same estimates of SMD and tau are provided of the Bayesian random effects model in figures 18 and 19.

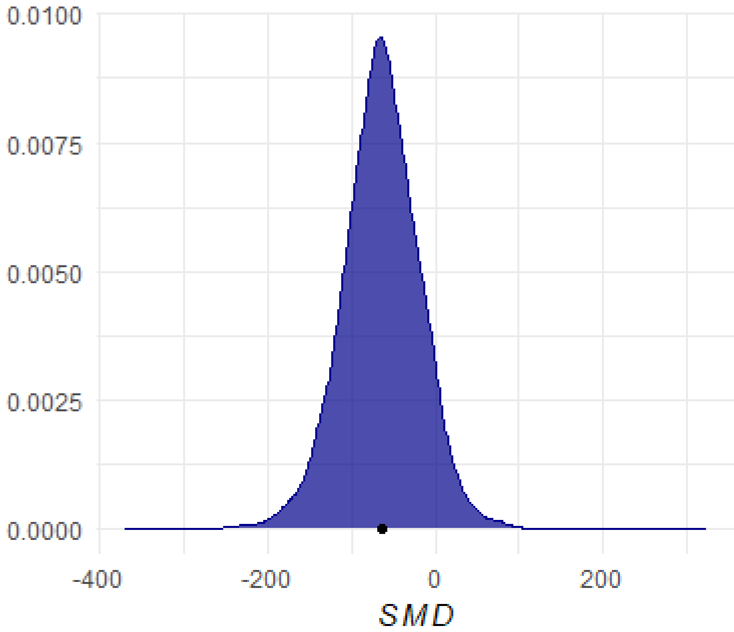


Figure 18 *Population Level Effects of Bayesian Model with Moderator Variables (SMD)*

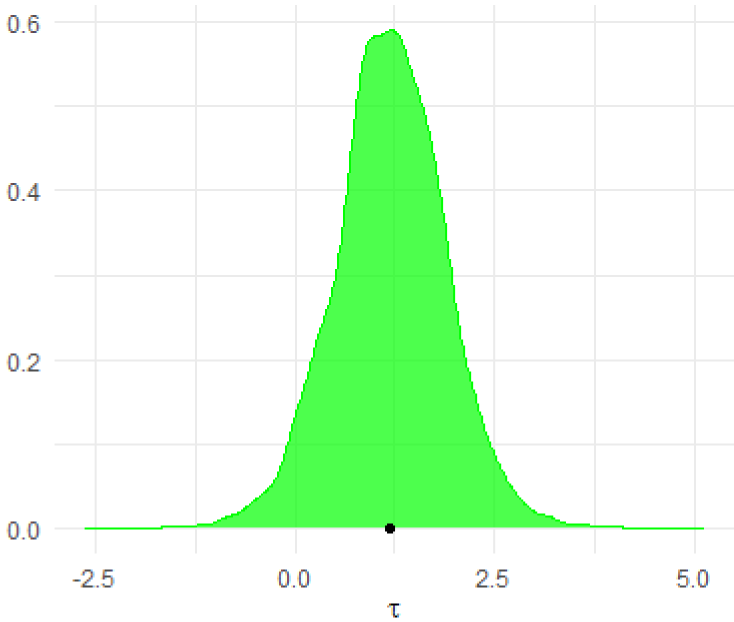


Figure 19 *Population Level Effects of Bayesian Model with Moderator Variables (tau)*

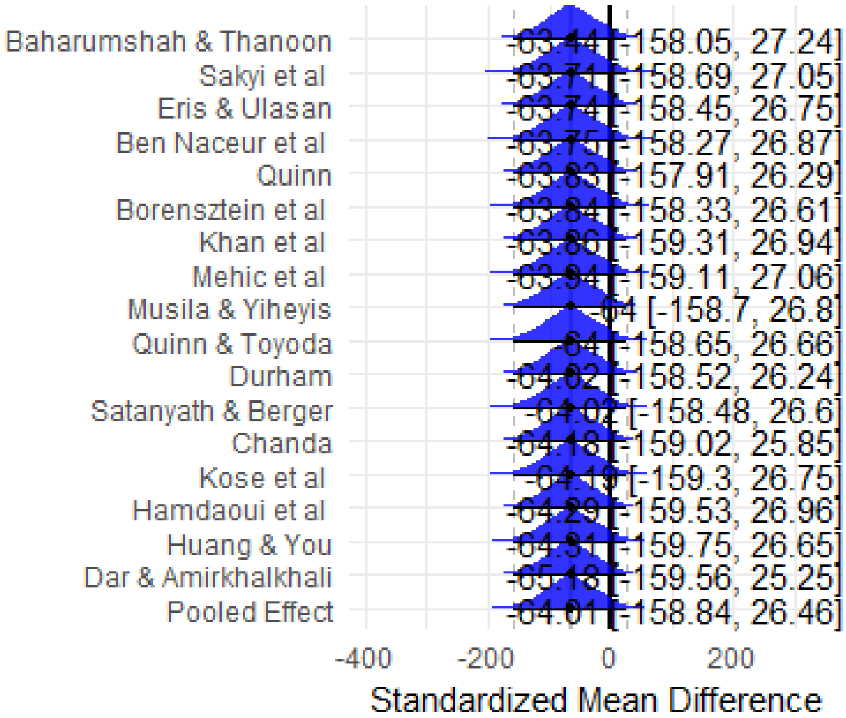


Figure 20 *Forest Plot of Pooled Effects, Bayesian Model with Moderator Variables, Probability Pooled Effect < 0.30 = 0.92625*

For interpretation of the forest plot of the pooled effects of the standardized mean difference (summary statistic) of the groups when moderator variables are added, it is important to understand how to interpret these types of plots in Bayesian regression, as they can be used to evaluate and communicate many important aspects of the model. First, for the consistency of the moderator effects, clustering around a common value is an indication that the moderator variables have a consistent effect across all studies. This indication is very clear in the plot for our model, we see heavy clustering around the negative 63 to negative 65 measure of standardized mean differences. The pooled effect size at the bottom of the plot in figure 20 signifies a combined estimate of the effect across studies, considering both the individual study estimates and their precision. This estimate of negative 64.01 is the same as the intercept estimate in the summary of the population-level effects. We can also use the forest plot to identify potential outliers of our studies that may warrant further investigation, but as we can see by the plot, there are no visible outliers given the ranges of the uncertainty interval of the pooled effect estimates, and we can therefore conclude that the sampled calculations are sufficiently good enough at measuring the mean differences, and that the moderators of the model all affect the study units the same. As with the frequentist mixed effects model, the estimated standardized mean difference suggests that the moderators affect the reported outcomes on economic growth negatively.

To better understand the effects of each individual moderator variable in the Bayesian analysis, there is provided a conditional effects plot in figure 21 showing the effects of each moderator as their individual values of x change and how this affects the PCC estimate of the reported outcomes.

For "time-span_years", previously described as the total amount of data coverage by each study in years, we can see clear spikes of uncertainty in the extremities of the variable (<10 and = 40), while we have the most precise estimates when the studies' total data coverage equals to about 25 years. This variable has been estimated to have very little effect on the reported outcomes between the independent and dependent variables of each study, and while that is a plausible estimate, the range of the plausible values (posterior distribution) is wide in the outer portions of the estimation. Overall, the moderator is thought to have a slight negative effect on reported outcomes as the data coverage increases, but based on the ROPE-test, one must accept the null value parameter, and thus can't deem it practically equivalent to real-world purposes.

For "Capital_Control", previously described as a dummy (= 1) for studies that have used the conceptualization "Capital Control" for their independent variable, we can see a negative development in the reported outcomes on economic growth if that specific conceptualization for the independent variable. The posterior distribution for the value Capital Control(x) = 1 is wide, meaning that there's some uncertainty to this estimate, plausibly because of a small number of studies where the assumption is met. The plausibility of reported outcomes being positive when the assumption is not met is high. Overall, one can say that using different conceptualizations of flow management techniques than capital control has positive effects on the reported outcome.

For "Pol_Sci", previously described as a dummy for studies written by at least one political scientist as one of the researchers, we can see clear positive developments in the PCC-value as we get closer to a political scientist writer. The posterior distribution is wide for political scientist writers and narrow for economist writers, meaning that there is more certainty in our estimates for economist writers. There is a general positive development in reported outcomes on economic growth when the writer is a political scientist as opposed to an economist. The estimations show that an economist will generally report outcomes close to a PCC of ~ 0.10, while political scientists generally would report estimates close to a PCC of ~ 0.25. Overall, we can say that political scientist writers have a positive effect on the reported outcomes of flow management techniques on economic growth.

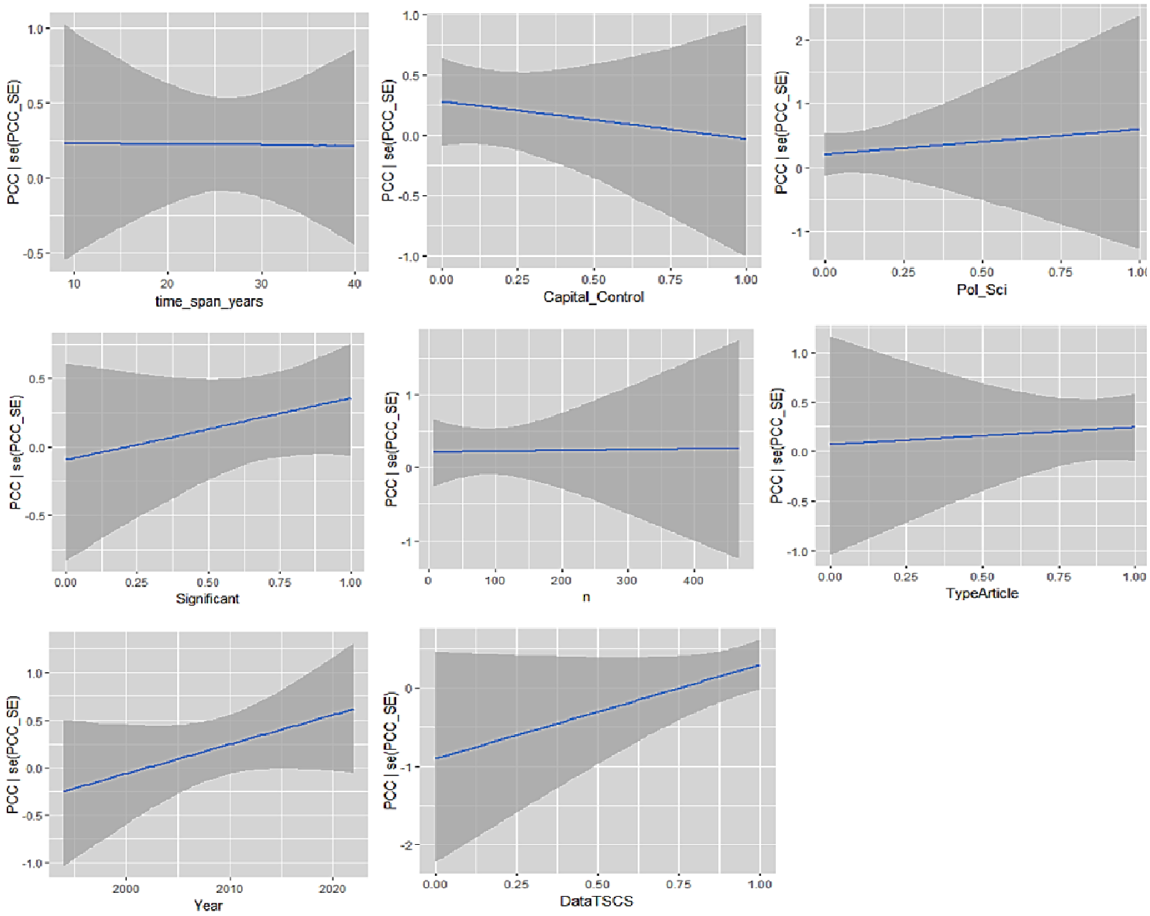


Figure 21 *Conditional Effects Plot of Moderator Variables in Bayesian Random Effects Model. The Blue Line Signifies PCC-Values for Each Value x of the given Moderator. Posterior Distribution Shown by Darkened Areas*

For "Significant", which previously is described as a dummy for significantly reported effects by authors of studies, there is a very steep development in the estimated PCC-value as results become significant. The posterior distribution is wider for insignificant reports, and narrower for significant reports, meaning that there is a wider range of plausible estimates for insignificant reports than significant. The estimated PCC is negative for insignificant reports, and positive for significant. Overall, we can say that significant results more often are reported as positive than insignificant results.

For "n", which is the total sample size of the estimated model where the reported outcome of independent variable on economic growth is extracted from in each study, the PCC-value is estimated to be slightly positive with a very gentle positive development in the reported outcomes as the sample size increases. The posterior distribution is narrow for small sample sizes and widens as studies have sample sizes above 200. The plausible estimates for high sample sizes thus have much higher variance than small sample sizes. Overall, one can say that the sample sizes of the initial studies have very little effect in small sample size-scenarios, and higher uncertainty in higher sample-sizes scenarios, but that the estimated PCC-value is almost visibly unchanged as the sample size increases.

The metadata consists of both articles and working papers, and “TypeArticle” is as previously described a moderator variable that represents a dummy for article-type publications, one can see a very slight positive development in the reported effects on economic growth from working papers to articles. The range of estimates in the posterior distribution of working papers is wide, probably because the sampled working papers constitutes a very small amount of the total sample, meaning there is higher uncertainty in the range of estimates for working papers as opposed to articles. Both working papers and articles are estimated to report positive outcomes on economic growth, but articles are estimated to generally report more positive effects than working papers.

“Year” simply represents the publication year of each given study, and as shown in the data-section of the thesis, there is good spread in the published studies from 1994 to 2022, which is also shown by more consistent estimates across the entire sampled posterior distribution of the moderator. There is a clear and steep development of the PCC-value from negatively reported effects to positively reported effects on economic growth as the years get closer to 2022. Overall, we can say that the plausibility of newer studies reporting positive effects is higher than older studies.

The last moderator variable in the plot, “DataTSCS”, is as previously described a dummy variable for time-series cross-sectional (panel) data as opposed to just time-series data. Very few of the studies used just time-series data, and this might explain why there’s very high variance in the sampled posterior distribution of DataTSCS = 0 (time-series), and very little variance for TSCS data, as most of the sampled studies used full panel data sets. Anyways, one can see estimates that are very strong negative on the reported effects on economic growth for studies that are using time-series data, and slightly positive estimates for TSCS-data. The development is steep, and overall, one can say that using TSCS for research has a very strong effect on the reported outcomes on economic growth.

5.5 Bayesian Model Evaluations

To test both the robustness, sensitivity and precision of the Bayesian models, several model tests have been conducted as described in the Methods-section of the thesis.

Sampling Test of Baseline Bayesian Model

One important assessment of Bayesian models is evaluating how the data has been sampled to ensure good sampling and thus more robust and accurate estimates. In figure 22, one can see the distribution of sampled data entries in the posterior distribution of the baseline Bayesian model. By "b_Intercept" and "sd_Author__Intercept", one can see that both the population-level and group-level samples are relatively normally distributed, meaning that there is no visible deviations from what we would expect in the distribution. This is also exaggerated by the fact that the distributions in the original data have already been evaluated to be relatively normal as by the QQ-plots in figures 9 and 10 of the frequentist models. Moreover, one can see that there is good spread of the sampling across all entries, and no visible clustering that induces bias in the posterior distribution.

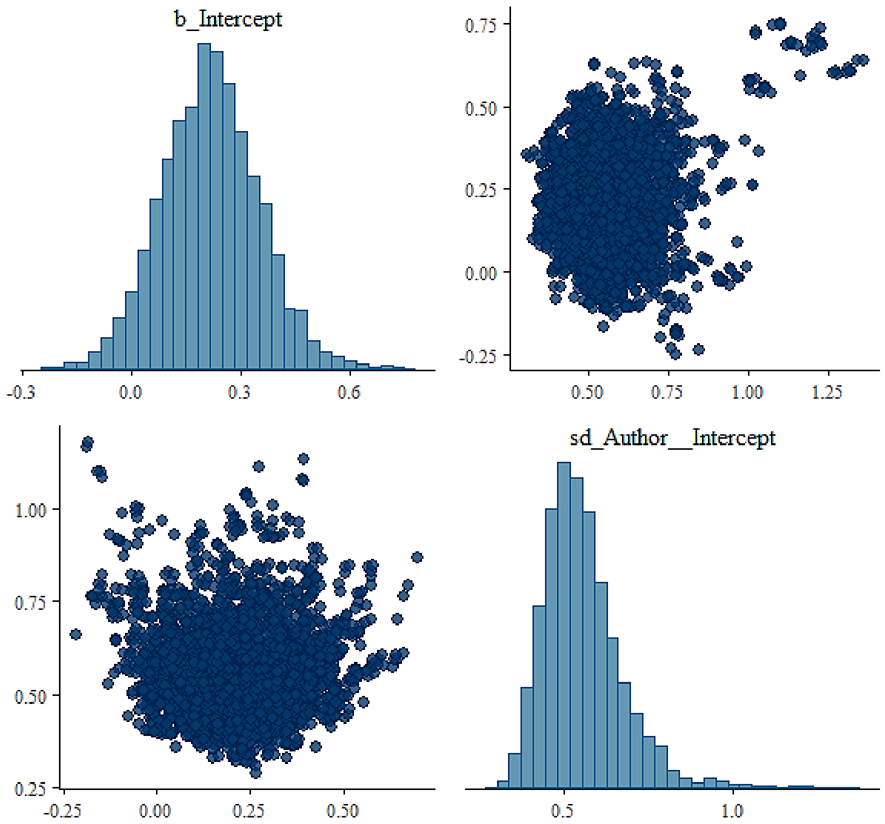


Figure 22 *Sampling Test of Baseline Bayesian Model*

Posterior Predictive Checks

To further investigate the posterior distributions and make sure that they are consistent benchmarks of the sample data, posterior predictive checks of the posterior distributions of both Bayesian models are shown in figures 23 and 24. By these plots, one can visibly see that the replications of data (in light blue lines) are almost identical to the sample data. This indicates good sampling of the priors and strengthens the validity and robustness of the Bayesian models.

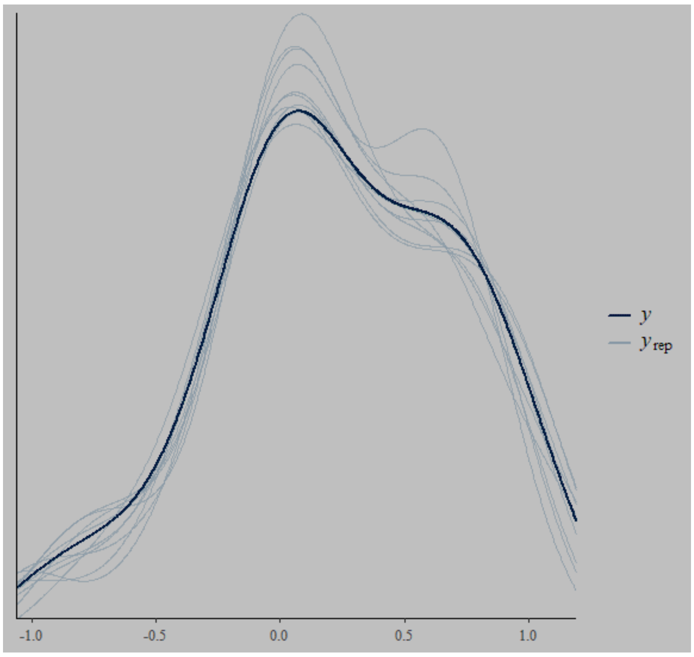


Figure 23 *Posterior Predictive Sampling Check of the Baseline Bayesian Model, y = real data,* y_{rep} *= replicated sample data*

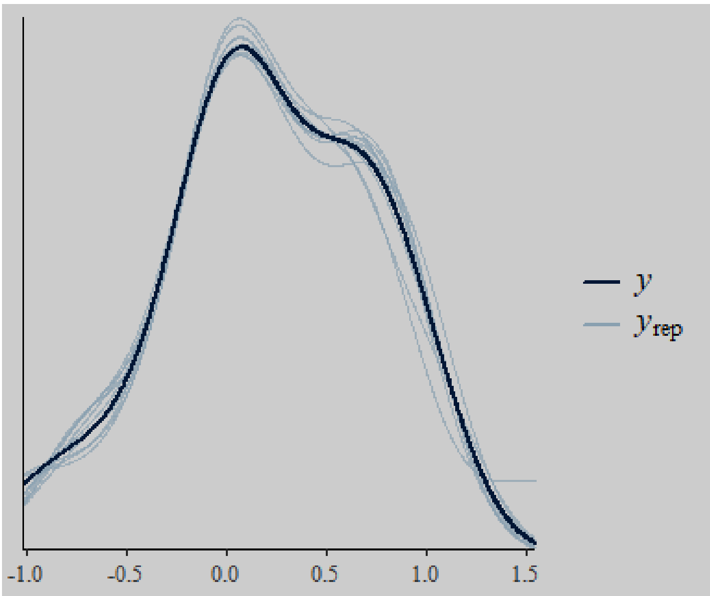


Figure 24 *Posterior Predictive Sampling Check of the Bayesian Random Effects Model with Moderators, y = real data,* y_{rep} *= replicated sample data*

Highest Density Intervals (HDI) and Equal-Tailed Intervals (ETI)

HDI, which previously has been defined as the interval values where values of a given parameter finds itself, and ETI, which has been defined as an equal probability interval of the observed below the lower limit and above the upper limit of the interval (Kruschke 2018, 270) are provided in tables 13 and 14 to ensure that the estimated credible intervals to the parameters are consistent across differing ways of measuring the credible intervals. As observed, the credible intervals are consistent across both HDI and ETI, meaning that the estimated errors in the initial models are plausible values of estimation. Most parameters have credible intervals that span from negative to positive, which means that one can base the assessments on the provided mean estimates to interpret the models.

Parameter	***95% HDI***
Intercept	-156.71, 28.18
DataTSCS (dummy)	-0.22, 2.55
Year	-0.02, 0.08
TypeArticle (dummy)	-1.06, 1.36
n (sample size)	-0.00, 0.00
Significant (dummy)	-0.49, 1.33
Political Scientist (dummy)	-1.52, 2.27
Capital Control (dummy)	-1.47, 0.71
Time Span in Years	-0.04, 0.04

Table 13 *HDI of Parameters on the Population Level*

Parameter	***95% ETI***
Intercept	-158.84, 26.46
DataTSCS (dummy)	-0.21, 2.57
Year	-0.01, 0.08
TypeArticle (dummy)	-1.04, 1.38
n (sample size)	-0.00, 0.00
Significant (dummy)	-0.45, 1.38
Political Scientist (dummy)	-1.54, 2.26
Capital Control (dummy)	-1.39, 0.79
Time Span in Years	-0.04, 0.04

Table 14 *ETI of Parameters on the Population Level*

6 Discussion

Going back to the research questions of this thesis, **"How do Global Capital Flows Affect Economic Growth?"**, three main research questions set the basis for further discussion. First, in order to help reach consensus on the effects of capital flow and management on economic growth, the first question asks:

1) *What is the mean observed effect of capital flow and capital flow management techniques on economic growth?*

Second, to help determine if there is publication bias present in the included journals and institutions who have published either the working papers or articles of the meta-regression analysis, the second question asks:

2) *Is there publication bias present in the published literature regarding the relationship?*

Finally, to help unfold why studies on capital flow and management come to differing conclusions on the effects, and figure out why, the third question asks:

3) *What are the drivers or between-study characteristics that may or may not cause differences in the reported outcomes between the relationship of capital flow and capital flow management techniques on economic growth in literature?*

The discussion chapter will as a main goal discuss the important and significant findings presented in chapter 5 "Results" related to these questions, but will also discuss the theoretical, practical and empirical implications induced by the findings of the thesis, as well as the limitations regarding the conducted study.

6.1 Model and Result Comparisons, Summary of Key Findings

The main models discussed and compared in this analysis are the meta-regression models of tables 4, 8, 9 and 10, which show the output parameters related to the frequentist fixed effects model, the frequentist mixed effects model and the Bayesian random effects models. The discussion will also be based on the results from the descriptive statistics and tests for publication bias.

The descriptive statistics developed of the study units in figures 4 and 5 show clear trends in an increasingly positive relationship between capital flows and management on economic growth. Where both figures showed an average effect around 0 in the beginning of the plot, or slightly negative below 0, the average effects' development show a rising trend where the average reported effect increases consistently in publications over time in the period from 1994 to 2022. The reasons behind these rising trends towards more positive associations between flow and growth are unclear, but they could for instance come from increased support for liberal policies, methodological or theoretical development, or they could be completely spurious and have no root in real-life development and trends.

Table 4, which presents the results from the frequentist meta-regressions, output an average or overall positive effect on economic growth of the study units of 0.07 in the frequentist fixed effects regression, meaning the one without moderators, indicating a slight positive effect on economic growth by capital flows. The calculated mean effect of the frequentist fixed effects regression is relatively low compared to the plausible estimate of the Bayesian Baseline Regression in table 8, where the estimated positive effect is 0.56. Both baseline models agree that there is a positive mean effect in the relationship between capital flow or capital flow management and economic growth based on the data drawn from the study units. These numbers are great for understanding the general magnitude of the effect between flow and economic growth, and as previously mentioned, the sample is not homogenous, meaning there is substantial variation in the real effects across the units. Based on the results from the Bayesian regressions standardized mean difference, the overall effect of flows on growth should be interpreted as higher than in the initial sample of the metadata.

In figure 4, from the frequentist mixed effects model with moderators, the average mean effect of the sample is calculated to negative 30.2, which is also a significant measure according to the model. This is a strong indication that the moderators, who to some degree account for the heterogeneity across the sample, affect the reported effects negatively in studies. The negative indication of the standardized mean differences is also present in the Bayesian model with moderators, as per tables 10 and 11. Here, the plausible estimate of the standardized mean effect is calculated to negative 64.01 when we account for moderator effects. Taking a closer look at Bayesian significance-testing considering the ROPE-test, only 0.08% of the 95% HDI falls within the ROPE, meaning that we can reject the null value. It is therefore a very precise and plausible estimate, indicating that the plausible estimate holds true value in practical terms, and we can use it for inferences in research. The probability of direction (pd-value) of table 11 is also estimated to 92.54%. Based on these assumptions and the consistent results of both models, we can be very certain that the included moderators of both models affect the reported outcomes very low negative on average.

There have been conducted several tests on the models themselves to evaluate how valid the inferences we can draw from them are. While the results of the testing from the Bayesian models were more robust and imposed higher explanatory power than the frequentist models, the results imposed that valid inferences can be drawn from all models. For the Bayesian models, sampling testing in figures 22, 23 and 24 gave adequately sufficient results, both from the posterior distributions and data points. ETI and HDI comparisons of tables 13 and 14 were also satisfactory. More tests were conducted on the frequentist models than the Bayesian, meaning we can more confidently assess the fit, robustness and validity of these models. First, QQ-plots were developed in figures 9 and 10 to test the distribution of the models against the normal, which they closely resembled. No potential outliers were identified, so the sample does not induce bias due to extreme values. Leverage plots in figures 11 and 12 of the fixed and mixed effects model indicated some bias in the fixed effects model, which leveled out in the field as the mixed effects model gained complexity with moderators, and no studies were omitted from the limited sample size. Based on the BP-tests of figures 13 and 14, the conclusion was that the models showed no clear signs of biased moderators, and evaluations could continue. The conducted LRT-test indicated high and significant improvements in the fit of the mixed effects (full) model compared to the fixed effects (baseline) model, and that mixed effects model should be preferred in drawing inferences due to a much better model fit by the additional moderators. In conclusion, both models fit the data sample well, especially the mixed effects frequentist model, and in hindsight, more tests should have been conducted on the Bayesian models to test their validity and robustness.

To the first research question on the mean observed effects of capital flow and capital flow management techniques on economic growth, the findings above highlight the nuances of the relationship, where it is influenced by contextual and methodological moderators of the empirical research. Overall, the trends and models suggest a positive association, but the presence of moderators emphasizes the importance of accounting for heterogeneity across study units of samples. Further research should delve deeper into the underlying mechanisms that drive the trends and elaborate on the complex dynamics of the relationship between capital flow and management and economic growth.

To further discuss the second research question regarding the presence of publication bias in the literature on capital flows and economic growth, assessments of funnel plots and the Egger's test were conducted on both frequentist models in table 3 and figure 6 and 7. The funnel plots showed indications of asymmetry due to high levels of standard errors in both of the models, and the conducted Egger's tests gave statistically significant results indicating that publication bias is present in the units of the sample. The calculated size of the publication bias for the fixed effects model was positive 0.0306, meaning that all things considered, there is a slight publication bias present for studies that report positive effects on the outcome between capital flows and economic growth.

Going to the effects of the moderator variables in the frequentist mixed effects model and the Bayesian random effects model as per the thirds research question, we can identify some interesting findings. In table 10, which is a summary of the Bayesian random effects model with moderators, all the population-level effects have been divided into groups, showing us the individual estimated effects to each moderator. These effects are also shown by the conditional effect plots in figure 21. An interesting, and also important finding related to this model, is that panel-data sets, meaning studies that use time-series cross sectional data as opposed to just time-series data, has a strong, positive estimated plausible effect on the reported outcome of a study on economic growth of 1.19. This effect is also prevalent in the frequentist regression of table 4, where it is estimated to have a strong, positive effect on the reported outcome of 1.26. The results are therefore consistent in both models. A Wald-statistic test was conducted on this variable in the frequentist regression and gave values that indicate a very high and clearly significant relationship to the outcome variable. Given the evaluations, both these findings are significant as per frequentist regression evaluation, and practically equivalent as per the Bayesian regressions ROPE-test. The parameter is also one of those between-study characteristics with the strongest positive effects overall, and one can therefore confidently assume that data type matters to the outcome of reported effects, and that studies utilizing panel-data will consistently and on average, report more positive effects on economic growth than studies using only time-series data. Given that the models have mixed and random effects, while being good fit to the data as per the testing, we can also assume that these inferences can be drawn to a larger population of study units than only the population of the data used analysis.

The next moderator that was included in the frequentist mixed effects regression of table 4 and the Bayesian regression of table 8 and figure 21 was the publication year of each article or working paper. The frequentist estimation gave a significant and positive effect estimate of this moderator variable of 0.01, while the Bayesian regression reported a plausible estimate of positive effect of 0.03. For the frequentist regression, this variable is in an alternative specification shown in table 7, where it was deemed insignificant. This might, as previously stated, be an indication that the frequentist model and this specific moderator is sensitive to changes in its specifications, and thus less robust. In the Bayesian regression, this variable converged to the data, and the HDI of the variable was 100% within the ROPE, meaning that we accept the null value of the parameter, and not deem it significant or draw any valid inferences from the plausible size of estimate to the real-world. The probability of the direction was however very high, with an above 90% probability that the direction of the effect is positive. These interpretations are also in line with the descriptive trends shown in figures 4 and 5, where there is a clear trend showing more positively reported effects on economic growth in more recent years than earlier publications. This could be an indication that the view of the relationship has changed since the earlier publications, either through methodological advancements or different measures, but this is hard to determine without doing a more specific analysis of the trends. The strong indications are that the assessments of the trends are correct, and that newer publications consistently report more positive effects on the relationship between flow and growth than earlier publications.

To assess whether publication type matters to the outcome of reported effect on economic growth, a dummy variable for articles as opposed to working papers was included in the models. For the frequentist mixed effects model, this moderator variable had a strong, significant effect. For the Bayesian random effects model, it converged to the data with an R-hat value of 1.00, it also had a rather large effective sample size. The 95% ETI and HDI ranges were also consistent. Assessing the ROPE-test, only 14.29% of the variable was within the ROPE-range, meaning we can reject the null value parameter and draw inferences from the plausible estimate. The frequentist model gave an estimated positive effect of 0.58, and the Bayesian model output a plausible positive estimated effect of 0.18. With these assessments in consideration, the inferences we can draw from the variable are quite strong. We can thus confidently say that articles as opposed to working papers, and regardless of the study unit population, whether this one or a hypothetical larger sample, in general will submit higher positive effects on the relationship between capital flow and capital flow management on economic growth. There might be several reasons for this. For instance, this might be an indication and stronger evidence of the previously concluded publication bias in journals for studies that report positive effects on the relationship. This could be argued, because journals more often publish articles than working papers, and if articles are more published, they would also be opposed to reporting negative effects to get published in the first place.

The effect of the sample size in the published literature was tested for being a relevant moderator in the reported outcomes on economic growth. In the frequentist regression, this variable had a significantly reported effect, and in the Bayesian regression model, it converged to the distribution, and was a 100% within the ROPE-range, meaning that we have to accept the null value parameter, and thus cannot draw any inferences from the estimate itself. The effects, however, were minimal. For the frequentist regression, the estimated effect was calculated to be very low negative, with a negative effect of 0.00, and the plausible estimate of the Bayesian model output a value of 0.000106, meaning slightly positive, but close to no effect. By looking at the conditional effect plot of figure 21, it is also very visible that the estimated effects are consistent across all values of sample sizes, but with greater uncertainty or range of plausible values of the posterior distribution in higher sample sizes. This could be an indication that even though the main assessment is that sample sizes virtually have little to no effect on the reported outcomes of economic growth, there is greater variation in the certainty as sample sizes increase. In further research, it might be clever to investigate this relationship to a greater degree in order to fully understand the consequences of sample sizes in study units on reported outcomes.

The next variable assessed in the models is the variable for reported significance-levels. As table 2 shows, 12 studies reported significant effects on the relationship between their independent variables and economic growth, while 5 studies reported insignificant effects. Significance is also an important aspect of assessing publication bias, which we have concluded to be present. The frequentist model reports a significant and positive effect of 0.54 from studies reporting significant effect on their independent variable and economic growth, while the Bayesian model reports a positive effect of 0.45. For the Bayesian "significance"-test of ROPE-testing, only about 10% of the HDI is within the ROPE, meaning that we can reject the null value parameter and draw valid inferences to the real-world from the parameter estimate. We also know that the effective sample size of the parameter is quite large, thus more precise, and the pd-value is high, meaning that we can be very certain in interpreting that the effect is positive. The assumption of these estimated parameters is therefore that there is a positive effect related to reporting significant effects on the relationship between capital flows and economic growth in research. In practice, this means that studies who report significant effects, also systematically report higher effects on the relationship of their independent variable of flow and economic growth.

Another important moderator that has been assessed in both full models is the variable describing the main research background of the author, mainly if they are political scientists or economists. As table 2 describes, only one of the authors was a political scientist, and this is thus a weakness of assessing and interpreting the results from this moderator, as there is little variation in the actual input values of the frequentist model, with only a sample size of seventeen, while the Bayesian accounts for this by computing a larger hypothetical sample size. The frequentist model estimated a positive effect of being a political scientist of 0.45, while the Bayesian model estimated a plausible effect estimate of 0.39, so the effects are quite similar, given the differences in (effective) sample sizes to each model. The ROPE-test of the Bayesian parameter gave decidable results of this variable, and the frequentist reported a significant effect. The pd-value of the Bayesian parameter was moderately high, with a value of about 67%, indicating that there is a significantly higher probability of the effect being positive than negative. The just interpretation after assessing these evaluations is therefore that it is a higher probability for political scientists to report more positive effects on their independent variable related to capital flow than their economist counterparts.

Given that conceptualizations presumably matter to the outcome of reported effects on economic growth, capital controls were tested as a dummy against other conceptualizations of the independent variable of each study unit, as capital controls are the main controlling policies that are induced to manage and regulate capital flows. This variable was tested both in the frequentist mixed effects model and the Bayesian regression model, as well as in an alternative specification of the frequentist model along with the previously mentioned variable of publication year of each study. This variable proved to be robust to changes in the alternative specification of the frequentist model, as it remained significant across both the full mixed effects model and the alternative specification model. In the main frequentist model, the variable had an estimated negative effect of 0.50, meaning a relatively strong negative effect on the reported outcomes of economic growth. This is an indication that when empirical researchers use capital controls as their main conceptualization of capital flow-regulating policies, they, on average, report effects 0.50 lower on the effects on economic growth compared to other conceptualizations such as FDI or purely capital flow. In the alternative specification of figure 21, the effect decreased to negative 0.07, but still significantly negative. The assessment is therefore that this variable is robust to changes when assessing model specifications and fit, but that the negative effects are exaggerated by other variables of the model. In the Bayesian assessment of this variable, an output plausible estimate negative effect of 0.31 was given, meaning that initially, it is in line with the frequentist assessment of a negative effect. The HDI is only partly within the ROPE-range as shown in table 11, and with a generally high pd-value, we can be certain about the direction of the variable as being negative. This assessment is also strengthened by the interpretation of the variable in figure 21, where we see a clearly negative development from value 0 to 1 of the variable. In terms, this means that researchers who use the conceptualization “Capital Control” as opposed to any of the other conceptualizations of the independent variable, consistently report more negative effects on economic growth, and given how we interpret random effects models, this conclusion can be drawn to a larger sample than only the data-sample in the thesis.

The last moderator variable accounted for, where there again are inconsistent results regarding the direction of the effect between the frequentist and Bayesian models, is the moderator measuring the time span of the data to each study unit. According to the frequentist model, there is a positive, significant effect of 0.01 to each increase of one year in the time span of data coverage, meaning that the effect grows quite large from low to high sample sizes. The Bayesian model reports a plausible estimated negative effect of 0.000472, which is very low negative for each increase in x, or a quarter of the estimated effect in the frequentist model. The Bayesian ROPE-test gives very insufficient results, with 100% of the HDI within the ROPE, meaning we have to accept the null value parameter and thus can't draw any inferences from the plausible estimate of the regression. However, the pd-value only gives an estimated certainty or plausibility of the direction of the negative effect of 50.91%. It is therefore hard to give a just assessment and evaluation of the variable based on the parameter evaluations alone. An option is to look for the strengths in each model, we now for instance that the hypothetical sample size of the Bayesian model is much larger than of the frequentist, and that could be an indication that inferences drawn from the Bayesian model is stronger. We also know that the explanatory strength of the Bayesian model is higher than of the frequentist due to sampling, and that we therefore should rely more on that model. The interpretation and assessments do so that we have to conclude that we can't safely draw any valid inferences of the effects time span of data has on reported outcomes on studies of economic growth.

Based on these assessments of the moderator variables, the effects they have on the reported outcomes are varying both in significance, magnitude and direction, and they also vary between models. Whereas all moderators are significant in the frequentist mixed effects model, the publication year, sample size and time span of data are deemed invalid to draw inferences from in the Bayesian model.

6.2 Interpreting the Findings

6.2.1 Theoretical Implications and Discussion of the Findings

The theoretical implications of the relationship between capital flow and economic growth reflect the complex and often contradictory nature of empirical findings in this domain. Capital flows, which include both inflows and outflows, are managed through various capital controls and financial policies that can either liberalize or restrict these movements, as mentioned in the theory section of the thesis. The positive theoretical implications are grounded in the notion that capital inflows can boost domestic investments, facilitate technological advancements, and enhance overall production capacities. This aligns with neoclassical and endogenous growth theories, where increased capital availability leads to higher economic output and growth through improved efficiency and innovation. For instance, the empirical analysis and MRA of this thesis confirms a positive relationship which might indicate that countries with liberalized capital markets and high foreign direct investment (FDI) experience sustained GDP growth, driven by enhanced technological capabilities and expanded production.

Conversely, the negative theoretical implications suggest that capital flow liberalization may lead to financial instability and economic volatility, particularly in emerging markets. The outflow of capital, while potentially beneficial in terms of international investment returns, can also deplete domestic capital reserves and increase vulnerability to external shocks. This perspective is supported by the Keynesian view that excessive foreign capital influence can undermine domestic economic stability. A hypothetical empirical analysis confirming a negative relationship might demonstrate that countries with high capital flow volatility, due to liberalized financial policies, experience frequent economic downturns and reduced long-term growth. Such findings would highlight the risks of capital flow liberalization, including reduced precautionary savings and increased susceptibility to global financial fluctuations.

These contrasting theoretical and empirical perspectives underscore the importance of nuanced policymaking in managing capital flows. Policymakers must balance the potential growth benefits of capital inflows with the risks of financial instability associated with capital outflows. The need for a comprehensive MRA becomes evident, as it allows for the synthetization of the varied empirical results of the study units by statistically adjusting for differences in study methodologies and measurements through PCCs and weighted precision of the units in the sample. This approach not only clarifies the broader implications of capital flow policies on economic growth but also provides a more robust foundation for policy recommendations aimed at fostering sustainable economic development when accounting for the overall effects of study units, and not singular case studies alone.

6.2.2 Practical Implications

The practical implications of the relationship between capital flow and economic growth, as evidenced by the meta-regression models and descriptive statistics in this analysis, are significant for policymakers and economists in decision-making processes. The frequentist fixed effects model indicates a slight positive overall effect of 0.07 on economic growth without considering moderators, while the Bayesian Baseline Regression presents a more substantial positive effect of 0.56. These results suggest that capital flow liberalization generally supports economic growth, aligning with the notion that capital availability can enhance investments and productivity. However, the mixed effects model introduces complexity; for instance, the frequentist mixed effects model with moderators indicates a significant negative average effect of 30.2, and the Bayesian random effects model estimates a negative effect of 64.01 when accounting for moderators. These findings highlight those specific factors, such as the nature of capital controls or the type of data used, that can significantly alter the impact of capital flows on economic growth in research, and that the moderators used in this analysis specifically, prompts studies to report more negative effects on the relationship.

From a practical perspective, these results suggest that while capital flow liberalization can be beneficial, policies and data must be managed carefully to mitigate potential negative effects. For instance, the positive effects in research of using panel data suggest that studies utilizing comprehensive data over time tend to report more positive impacts on economic growth, indicating that robust data analysis can better capture the benefits of capital flows. Additionally, the analysis indicates potential publication bias by the funnel plots and Egger's tests, and as articles are more likely to report positive effects than working papers, is therefore underscoring the need for critical evaluation of published research. The findings also emphasize the importance of considering methodological differences and the specific contexts of capital flow management policies when drawing conclusions about their effects on economic growth.

In conclusion, on the practical implications, while liberal capital flow policies can stimulate economic growth, their designs and implementations must consider the heterogeneous effects observed in different studies and account for this before implementation. Policymakers should ensure that capital flow management strategies are tailored to the specific economic conditions and the quality of the data that is accessible, as well as be aware of potential biases in the literature that may skew the perceived benefits or drawbacks of these policies. This nuanced approach can help harness the positive aspects of capital flows while minimizing the associated risks, leading to more stable and sustainable economic growth.

6.2.3 Empirical Implications

The empirical implications derived from this analysis of has many sides offering insights into the variability and context-dependency of the observed effects of the study units in the analysis. The MRA-models reveal significant heterogeneity in the impact of capital flows on economic growth, suggesting that empirical studies must carefully account for contextual factors such as the type of data used, the specific policies examined, and publication biases in literature. For instance, while the frequentist fixed effects model shows a slight positive overall effect, the inclusion of moderators in mixed effects models reveals substantial negative effects, highlighting the importance of considering interaction effects and the specific characteristics of each study. The finding that panel data studies tend to report more positive effects suggests that more comprehensive data over time might better capture the benefits of capital flows, pointing to the necessity for robust, longitudinal data in empirical research.

Furthermore, the significant variation in reported outcomes based on publication type indicates a potential bias in the literature, where journal articles might disproportionately report positive effects compared to working papers. This bias needs to be addressed in empirical research to provide a more balanced understanding of the relationship between capital flows and economic growth. The strong negative effects reported for studies focusing on capital controls as independent variables suggest that restrictive policies might have more adverse impacts than previously understood regarding flow and growth, emphasizing the need for nuanced and context-specific policy evaluations. Additionally, the inconsistency between frequentist and Bayesian models regarding the time span of data used emphasizes the need for methodological rigor and the importance of cross-validating results with different statistical approaches.

Overall, these empirical implications underscore the complexity of the relationship between capital flows and economic growth and highlight the need for detailed, context-aware analyses. Researchers should strive for methodological robustness, consider potential biases, and ensure comprehensive data collection to accurately assess the impacts of capital flow policies, while still exploring and finding new ways to examine the relationship, either through methodological or theoretical innovations. This nuanced understanding can inform more effective and tailored economic policies, ultimately fostering sustainable long-time growth in the domestic economies where they are implemented.

6.3 Limitations of the Study

There are several limitations of this which create the need for careful consideration to contextualize the findings correctly. Firstly, the heterogeneity of the sample poses a significant challenge; the diverse range of study units and varying methodological approaches lead to substantial variation in reported effects, making it difficult to generalize the findings universally across other empirical populations. While the meta-regression models attempt to account for this heterogeneity through moderators, the robustness of these adjustments can be questioned given the inherent complexities in standardizing measures across different contexts and datasets. Additionally, the presence of publication bias, as indicated by the consistent difference in the initial assessments of the analysis, as well as the reported outcomes between journal articles and working papers and publications reporting significant results, suggests that the literature may be skewed towards more favorable results, potentially overestimating the positive impact of capital flows on economic growth.

Moreover, the reliance on reported significance levels and publication years as moderators highlights another limitation: the potential for time-related biases and evolving methodological standards, which can affect the consistency and reliability of reported effects over time. The inconsistency between the frequentist and Bayesian models regarding the effect of data span further complicates the interpretation, indicating that different statistical approaches might yield divergent conclusions. This divergence points to the need for cross-validation and cautious interpretation of results in empirical assessments of capital flows and economic growth.

Another limitation is the relatively limited sample size of studies, particularly those authored by political scientists, which limits the ability to draw robust conclusions about the influence of disciplinary background on the reported outcomes. Furthermore, the significant negative effects associated with the use of capital controls as a conceptual framework underscores the complexity of policy impacts, yet the reasons behind these negative effects remain unclear and warrant further investigation. Lastly, while the thesis employs innovative and complex statistical techniques, the potential for unobserved confounders and omitted variable bias cannot be entirely ruled out, suggesting that the results should be interpreted with caution and as part of a broader, ongoing research agenda into the dynamics of capital flows and economic growth. Lastly, the reader should account for potential mistakes by the author of this thesis given the large magnitude of the work, as in all research. Mistakes related to the methodological analysis and development and coding of data can occur, as a vast amount of literature has been processed, however, precautions have been taken to largely minimize the risk of such mistakes.

7 Concluding Remarks and Guidance for Further Research

Capital flows and economic growth is a complex and dynamical relationship in an increasingly interconnected economic and financial world where moving capital across borders is a defining feature of, fostering the need for meta-analysis on the topic. To my knowledge, this is the first meta-analysis on the topic, at least in a quantitative direction through meta-regression analysis. Due to the profound implications global capital flows have on economic growth, it is crucial to provide a better understanding of the relationship. Innovation-wise and to my knowledge, it is also one of the first, if not the first of studies in political research and comparative politics combining and comparing frequentist and Bayesian MRA as the main research methodology, allowing for a deeper understanding of the dynamics on both a given and a hypothetically larger population.

The thesis has set out to answer one main research question regarding the relationship between capital flows and economic growth in research, which is addressed by the key findings of the analysis of seventeen studies in the period 1994-2022, and the interpretations and implications introduced by the discussion. The thesis addresses the overall effects of capital flows and economic growth, and the statistical models of the MRA suggest an overall positive effect of capital flow and capital flow management on economic growth, both when assessing the question through frequentist and Bayesian MRA-models. The frequentist model is a fixed effect model which accounts for the population of the sample, and the Bayesian model is a random effects model accounting for a hypothetical larger population of sample units. These inferences are therefore valid on both the limited sample of the thesis and on a larger set of hypothetical research population. The trends were presented in the descriptive statistics of the thesis, where a rising trend of positively reported effects on economic growth from capital flows was present in the period from 1994 to 2022 of data and could be an indication of stronger support for liberal economic policies as growth-inducing in contemporary research and politics. When accounting for heterogeneity through between-study characteristics or moderators, the estimated overall effects and standardized mean differences indicate that the moderators in general affect the reported outcomes on economic growth in a negative direction, meaning that the relationship in empirical research is largely influenced by the contextual and methodological factors surrounding it. Second, on the question of publication bias, the statistical assessments of the funnel plots and conducted Egger's test indicates a slight bias for studies reporting positive effects more likely to be published in academic journals. Third, regarding how key moderator variables affect the reported effects on economic growth, there are consistent results in the assessments of all moderators in the frequentist and Bayesian models except the publication year, sample size and timespan of data, where the Bayesian model deem them to not be practically equivalent to real-world interpretations through assessments of the statistics.

The implications discussed in the latter part of the thesis reflects the complexity in the relationship of capital flows and management on economic growth, where theoretically, both positive and negative implications are supported, which is also supported by the empirical analysis and survey of previous findings where positive effects have been observed under liberal markets and high FDI, while negative effects have emerged in the contexts of financial stability and political volatility. This further poses some practical implications, as the thesis has concluded with a generally positive relationship on the relationship, but severely negative impacts when accounting for specific factors, indicating that in order to accurately assess policy impacts by liberalizing capital flows, robust data analysis and critical evaluations of existing research is inevitable to confidently draw valid inferences. Along with these implications, the importance of context-awareness in empirical analyses should be highlighted due to the heterogeneity of the data, where the analyses should account for as many and varying contextual factors in their data as possible. The inconsistent results among the study units utilizing different methods, models and measures underscores the need for methodological testing and cross-validation to create a balanced understanding of the implications of economic and financial policy.

While capital flow liberalization can foster economic growth, the heterogeneous effects observed in different studies on flow and growth highlight the need for specifically tailored and nuanced policy approaches, where policymakers should consider the specific economic conditions, data quality in their analysis of the implications, and potential biases when designing and implementing capital flow management strategies in domestic and foreign economies. Further research, employing robust and innovative methodologies, is essential to deepen our understanding of this relationship and inform the implementation of effective economic policies that promote sustainable growth and mitigate potential financial risks and instability.

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8 Appendix

See supplementary files for the raw-data and R-code essential for replicating the study, ensuring transparency of the results of the analysis.