The AI Capital Control Index

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Abstract

We construct a novel event-level Capital Control Measures (CCM) dataset covering 196 countries from 1999 to 2023 by leveraging prompt-based large language models (LLMs). The dataset enables high-frequency empirical analysis and cross-country comparisons based on rich policy attributes, including action type, intensity, direction, implementing authority, and policy scope. Using a two-step prompt framework with GPT-4.1, we extract structured information from the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions* (AREAER), resulting in 5,198 capital control events annotated with 27 policy fields and accompanying model reasoning. To facilitate real-time classification and extension to external policy sources, we further fine-tune an open-source Meta Llama 3.1–8B model, *CCM-Llama*, trained on AREAER change logs and final status reports. The model achieves an accuracy of 90.09% in policy category classification and 99.55% in policy status prediction.

We illustrate the empirical value of the CCM dataset using a global monthly country-level panel to examine how capital control interventions affect cross-border fund flows. Moving beyond country-specific event studies, we document robust average effects of capital control measures while explicitly accounting for policy intensity, composition, and discrete policy adjustments. The results show that restrictive capital control measures are systematically associated with fund outflows, particularly during episodes of forceful tightening and salient policy changes, whereas liberalizing measures exhibit weaker and less robust effects. While financial development is an important determinant of baseline capital mobility, we find limited evidence that it systematically amplifies the short-run effects of capital control interventions.

Overall, this paper contributes to the growing literature on LLM-assisted measurement in economics by providing a high-frequency, event-level global policy dataset and a scalable, replicable framework for automated classification of capital control measures from complex and evolving textual sources.

JEL codes: F32, F36, G15, C55.
Keywords: Capital controls; Capital flows; Large language models; Policy measurement

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1 Introduction

Capital controls play an essential role in the literature on international capital flows. However, understanding their causes and consequences requires high frequency data with detailed information on the kind of interventions adopted, including their policy target, intensity and direction. Current data on capital controls lacks this granularity, and is very costly to generate in terms of human resources.

In this paper we address these challenges by constructing a new Capital Control Measures (CCM) database covering 196 countries from 1999 to 2023 using artificial intelligence. The database has high frequency, is available at a high level of granularity, and can be easily updated as new capital controls are adopted.

1.1 Motivation and Literature

To mitigate the spillover effects of monetary policy from other countries and reduce financial instability, governments often impose restrictions on capital mobility, regulating capital inflows and outflows across different financial accounts. Figure 1 illustrates the absolute volume of various types of capital flows from the OECD monthly capital flow dataset. While global capital flows have generally increased since 1995, different financial accounts have exhibited significant fluctuations, especially during major crises such as the 2008 financial crisis and the COVID-19 pandemic. During those periods, capital control interventions played an important role in global capital flows (Erten et al., 2021).

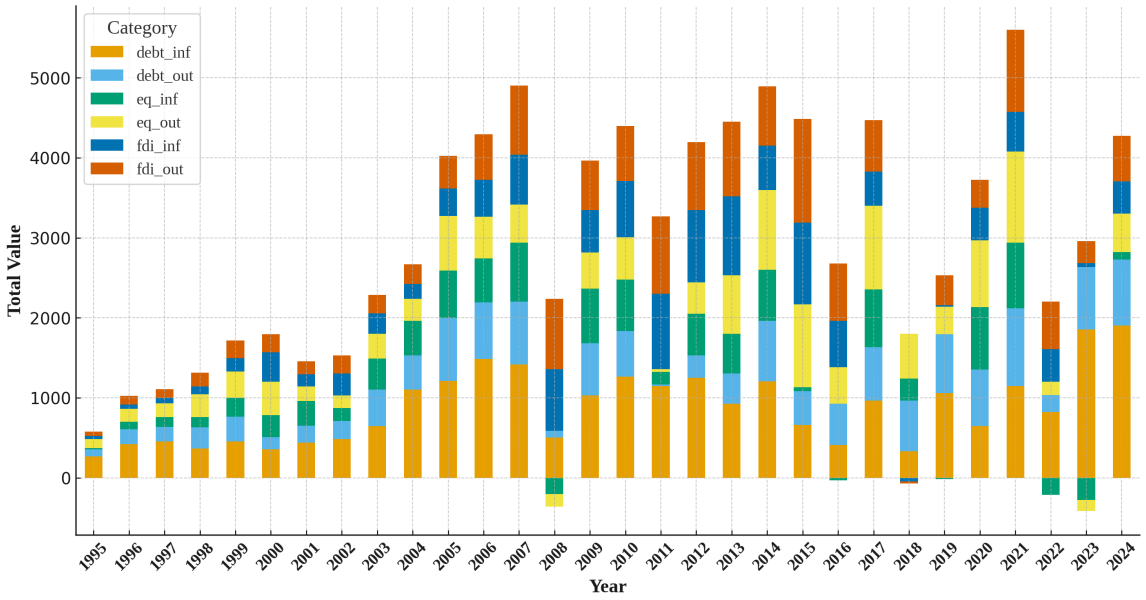


Figure 1. Global Capital Flow Volume

Notes: Data from the OECD Monthly Capital Flow Dataset (Lepers and Crescenzio, 2024), where debt inf represents gross portfolio debt inflows, capturing the total value of debt securities acquired by foreign investors; debt out denotes gross portfolio debt outflows, measuring the volume of domestic investments in foreign debt instruments. Similarly, eq inf and eq out correspond to gross portfolio equity inflows and outflows. Additionally, fdi inf and fdi out indicate gross foreign direct investment (FDI) inflows and outflows. These variables provide a comprehensive view of international capital mobility across different asset classes.

There is a large and growing literature examining the effectiveness of capital control policies, which finds that heterogeneity of capital control measures is important for understanding their impact. Klein (2012) finds that, in the face of heightened uncertainty, central banks in developing countries often resort to imposing restrictions on capital outflows. Similarly, Bruno et al. (2017) document that capital flow management interventions targeting the banking sector were effective in slowing down banking inflows in a sample of 12 Asia-Pacific economies during the period 2004–2013. More recently, several studies have highlighted the conditional nature of capital control effectiveness. Rebucci and Ma (2019) provide a comprehensive survey and argue that the success of capital controls depends critically on factors such as institutional quality, the timing of the intervention, and the type of capital flow targeted. Similarly, Bergant et al. (2024) show that, relative to macroprudential regulation, capital controls have a weaker impact on macroeconomic stability. Focusing specifically on capital outflows, Chang et al.

(2024) investigate capital controls on outflows (CCOs) during periods of financial distress, finding that government credibility and reputation are essential for their successful implementation. Forbes et al. (2015) find that while certain capital flow management measures—such as removing outflow controls—may help mitigate real exchange rate appreciation, most CFMs have limited impact on key macro-financial variables and often fall short of achieving their stated policy objectives. In addition, recent work also explores the interaction between capital controls and other policy domains. Lloyd and Marin (2024), for instance, show that capital control measures and trade policies are closely linked: optimal capital controls tend to be smaller when trade policy is constrained by agreements such as FTAs, though under certain conditions they may be larger depending on macroeconomic fundamentals.

Thus, the existing literature underscores the importance of heterogeneity in capital control measures in shaping cross-border capital flows. By looking into the data used in the empirical analysis, most empirical studies rely on index-based approaches to capture the presence or intensity of capital controls. A prominent example is the dataset constructed by Quinn and Toyoda (2008), Fernandez et al. (2016), who use the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) to produce binary indicators of capital control measures by asset class and country. These indicators are derived from the "status" column in the AREAER reports, which flags the presence of capital restrictions using a "Yes/No" format.[1] Based on this information, they construct annual indices taking values between 0 and 1 to reflect the existence of restrictions across categories. The binary construction implicitly treats all capital control measures as equally binding or consequential, masking the variation in intensity, scope, and implementation detail. Related indices such as the Chinn-Ito index (Chinn and Ito, 2005) and its extensions (Schindler, 2009) also rely on binary information from the AREAER to produce aggregate measures of financial openness. While useful for identifying broad trends, these indices abstract from the underlying heterogeneity of capital control instruments and do not distinguish between liberalizing and restrictive interventions or account for conditional policies.

[1]The AREAER includes a column labeled "status" that provides a binary indicator of whether a given restriction is in place.

1.2 Limitation of Current Measures

As a result, current capital control indices face three key limitations. First, they are typically available only at low frequency; second, they provide limited information about the characteristics of the underlying policy interventions. By relying on binary classification, existing indices may obscure meaningful variation in the content of capital control measures, treating qualitatively distinct interventions as equivalent. While this approach is tractable, it risks overlooking important differences in the design, scope, and enforcement of capital controls. To contribute to a more detailed understanding of policy dynamics, we develop the Capital Controls Measures (CCM) Dataset, a new event-level dataset enriched with multiple policy characteristics by leveraging textual analysis using prompt-based large language models (GPT-4.1).[2] By integrating these dimensions, our CCM dataset captures event-level capital intervention measures and characterizes each policy action, offering a more granular and multidimensional view of capital control measures over time.

Third, another major challenge in current capital control research is the costly and labor-intensive nature of data construction. Traditional indices rely on manual review of the AREAER reports, where researchers must examine each policy announcement to determine whether it belongs to a particular category, constitutes an exemption, or reflects potential misclassifications. This procedure is both time-consuming and expertise-intensive, and is tied to annual reporting cycles, which delay access to up-to-date information for relevant organizations and researchers and restrict the frequency of available data. Furthermore, each regulatory action must be individually assessed and coded, adding considerable complexity to the process. To address these limitations, leveraging generative AI, we develop and finetune an open-source LLM called *CCM-Llama*, which offers a novel yet practical alternative to the previous labor-intensive data construction, by automating the assignment of capital intervention policies to the appropriate IMF-aligned categories. This approach improves both the efficiency and scalability of capital control measures data collection, while enabling more detailed and real-time and multi-source policy analysis.

[2]Our dataset relies on the textual description of each policy to provide attributes such as whether a measure is restrictive, conditional, or liberalizing; whether it is implemented at the national or sub-national level; and which sectors or countries are targeted, among other features.

1.3 Paper Structure

The remainder of the paper is organized as follows. Section 2 outlines the textual analysis methodology using prompt-based LLMs and presents key stylized facts derived from the CCM dataset. Section 3 details the finetuning process of an open-source LLM and evaluates its performance in classifying capital control measures. Section 4 illustrates an event-study application of the CCM dataset, examining the effectiveness of capital control policies on global fund flows. Section 5 concludes.

2 Textual Analysis of Capital Control Measures with Prompt-Based LLMs

In this section, we leverage textual data on capital controls from the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions* (AREAER) and apply pre-trained large language models (LLMs) to extract multidimensional information about capital interventions. The AREAER provides narrative descriptions of policy changes for each country, including the nature, scope, and context of capital account regulations. By combining domain-specific prompts with the reasoning capabilities of LLMs, we instruct the LLM to identify key features of each intervention. This approach enables us to construct a structured, event-level dataset that captures both the timing and characteristics of capital control actions at a daily frequency.

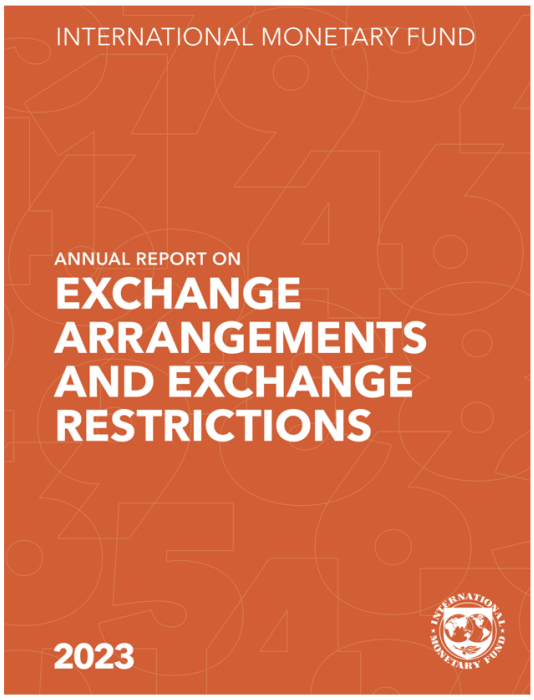
2.1 Textual Data Description

Our main source of country-level textual data comes from the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions* (AREAER), spanning the years 1999 to 2023 for 196 countries. The AREAER provides standardized, annually updated documentation across 12 main sections, covering topics such as national exchange rate regimes and detailed legal and administrative descriptions of capital account regulations. Each report contains over 250 subcategories per year, offering granular policy information for a wide range of instruments and regulatory dimensions.

In addition to these structured elements, the AREAER includes narrative descriptions of policy changes that document the adoption, amendment, or removal of specific measures [3]. These change records are organized by section and typically report the effective date of implementation. Precise timing is essential for conducting event-study analyses, as it allows researchers to align policy interventions with market responses or macroeconomic outcomes at high temporal resolution. The combination of consistency in reporting and the richness of unstructured description text makes the AREAER particularly well suited for information extraction and classification using large language models [4].

[3] Refer to the AREAER online platform:About Us

[4] Between 1999 and 2022, the structure of the AREAER underwent several revisions, including the discontinuation of certain categories and the introduction of new ones. We account for these



ALBANIA

Surrender requirements	No.	
Surrender to the central bank	No.	
Surrender to authorized dealers	No.	
Restrictions on use of funds	No.	
		Capital Transactions
Controls on capital transactions	Yes.	In accordance with the regulation on foreign exchange activities, the transfer of capital from abroad by residents and/or nonresidents may be carried out freely and without restrictions. Capital transfers outside Albania for account holders licensed by the BOA may be performed on the authority of their respective institutions and in accordance with the regulatory and supervisory requirements of the BOA. License holders may make transfers outside Albania for their customers with the requisite documentation in the BOA's regulation on foreign exchange activities.
Repatriation requirements	No.	
Surrender requirements	No.	
Surrender to the central bank	No.	
Surrender to authorized dealers	No.	
Controls on capital and money market instruments	Yes.	Transactions with securities and other similar instruments, and the exercise of rights arising from the latter, may be carried out only through banks and/or other institutions authorized by law, on the basis of a contract. For prudential reasons and money-laundering prevention, the FIU and the BOA monitor and review these transactions.
On capital market securities	Yes.	
Shares or other securities of a participating nature	Yes.	Law No. 62 of May 14, 2020, "On capital markets" requires the regulated market to establish rules and criteria relating to transactions on the market and the admission to trading of shares or other securities. The rules of the Albanian Securities Exchange, which operates a regulated market, specify the criteria for the listing and admission to trading of shares and other securities, as well as the characteristics of different classes of financial instruments for the admission to trading on the different market segments which it operates. Where a shareholder acquires or disposes shares of an issuer whose shares are admitted to trading on a regulated market, such shareholder notifies the issuer if the proportion reaches, exceeds, or falls below the thresholds as specified in Regulation No. 5 of January 26, 2023, "On transparency requirements of listed companies".
Purchase locally by nonresidents	No.	Law No. 62/2020 "On Capital Markets," in force since September 1, 2020, does not impose any restrictions on the local purchase of securities by nonresidents.
Sale or issue locally by nonresidents	Yes.	Issuing securities with purpose of soliciting funds from the public is not allowed in Republic of Albania, without a valid prospectus in accordance with the Capital Market Law and respective bylaws. Securities may only be offered to the public and admitted to trading in the Republic of Albania after prior publication of a prospectus in accordance with the applicable capital market law and regulations. The obligation to publish a prospectus applies to both equity and

Figure 2. Example of AREAER Reports

Notes: This picture is an example of 2023 AREAER report from IMF online platform: click here

As demonstrated in Figure 2, the AREAER is updated annually on the IMF's official website[5]. Each report includes narrative descriptions of capital transaction controls and financial sector measures implemented by individual countries. These entries are organized by category index, category name, a corresponding textual description, and a binary status indicator. Table 1 summarizes the distribution of capital control measures and recorded changes across the full set of AREAER reports used in our analysis.

Category We follow the IMF AREAER classification under Section XI.A, which outlines controls on cross-border capital transactions. Our focus is on subcategories XI.A.2 through XI.A.7, covering various instruments and transaction types. Specifically, XI.A.2 addresses controls on capital and money market instruments

structural changes by mapping discontinued categories to consistent equivalents where possible to maintain comparability.

[5]The most recent AREAER report covers all policy changes through 2022 and was published in 2023.

Table 1. Total Count and Word Count of Capital Control Descriptions by Year

Year	Panel A: Description on Final Report		Panel B: Description on Yealy Changes	
	Count	Word Count	Count	Word Count
1999	1111	9872	—	—
2000	1116	8128	59	1615
2001	1116	8531	75	1991
2002	1122	8867	78	2327
2003	1122	8970	90	2424
2004	1122	9680	79	1915
2005	1122	9962	30	908
2006	1128	11505	102	3079
2007	1128	12083	145	4671
2008	1128	11827	121	4082
2009	1134	13639	92	3708
2010	1140	15628	85	4059
2011	1140	17022	94	6369
2012	1146	17359	97	4511
2013	1140	16149	143	7938
2014	1146	18512	162	7545
2015	1152	22779	222	13852
2016	1146	19444	270	19894
2017	1152	20447	337	21686
2018	1152	20097	241	14701
2019	1152	19486	414	28793
2020	1158	20565	347	21825
2021	1164	21441	385	25115
2022	1164	21697	436	21306
2023	—	—	343	22218

such as equities, bonds, and mutual funds; XI.A.3 covers derivatives and other financial instruments; XI.A.4 pertains to credit operations, including financial and commercial credits as well as guarantees; XI.A.5 focuses on direct investment, including both inward and outward FDI and the liquidation of such investments; and XI.A.7 relates to real estate transactions. These subcategories are further disaggregated by investor residency (resident vs. nonresident), direction of capital flow (inward vs. outward), and the nature of the instrument. The complete list of 45 category indices and corresponding names is provided below.[6]

[6]The indices and names follow the official classification used in the IMF AREAER.

```
("XI.A", "Controls on capital transactions"),
("XI.A.2", "Controls on capital and money market instruments"),
("XI.A.2.a", "On capital market securities"),
("XI.A.2.a.1", "Shares or other securities of a participating nature [eq]"),
("XI.A.2.a.1.i", "Purchase locally by nonresidents [eq_plbn]"),
("XI.A.2.a.1.iv", "Sale or issue abroad by residents [eq_siar]"),
("XI.A.2.a.1.iii", "Purchase abroad by residents [eq_pabr]"),
("XI.A.2.a.1.ii", "Sale or issue locally by nonresidents [eq_siln]"),
("XI.A.2.a.2", "Bonds or other debt securities [bo]"),
("XI.A.2.a.2.i", "Purchase locally by nonresidents [bo_plbn]"),
("XI.A.2.a.2.iv", "Sale or issue abroad by residents [bo_siar]"),
("XI.A.2.a.2.iii", "Purchase abroad by residents [bo_pabr]"),
("XI.A.2.a.2.ii", "Sale or issue locally by nonresidents [bo_siln]"),
("XI.A.2.b", "On money market instruments [mm]"),
("XI.A.2.b.1", "Purchase locally by nonresidents [mm_plbn]"),
("XI.A.2.b.4", "Sale or issue abroad by residents [mm_siar]"),
("XI.A.2.b.3", "Purchase abroad by residents [mm_pabr]"),
("XI.A.2.b.2", "Sale or issue locally by nonresidents [mm_siln]"),
("XI.A.2.c", "On collective investment securities [ci]"),
("XI.A.2.c.3", "By residents to nonresidents [cio]"),
("XI.A.2.c.1", "By nonresidents to residents [cii]"),
("XI.A.3", "Controls on derivatives and other instruments"),
("XI.A.3.a", "Purchase locally by nonresidents"),
("XI.A.3.b", "Sale or issue locally by nonresidents"),
("XI.A.3.c", "Purchase abroad by residents"),
("XI.A.3.d", "Sale or issue abroad by residents"),
("XI.A.4", "Controls on credit operations"),
("XI.A.4.b", "Financial credits [fc]"),
("XI.A.4.b.1", "By residents to nonresidents [fco]"),
("XI.A.4.b.2", "By nonresidents to residents [fci]"),
("XI.A.4.a", "Commercial credits"),
("XI.A.4.a.1", "By residents to nonresidents"),
("XI.A.4.a.2", "To residents from nonresidents"),
("XI.A.4.c", "Guarantees, sureties, and financial backup facilities"),
("XI.A.4.c.1", "By residents to nonresidents"),
("XI.A.4.c.2", "To residents from nonresidents"),
("XI.A.7", "Controls on real estate transactions"),
("XI.A.7.a", "Purchase abroad by residents"),
("XI.A.7.b", "Purchase locally by nonresidents"),
("XI.A.7.c", "Sale locally by nonresidents"),
("XI.A.5", "Controls on direct investment [di]"),
("XI.A.5.a", "Outward investment [dio]"),
("XI.A.5.b", "Inward direct investment [dii]"),
("XI.A.5.c", "Liquidation of direct investment [ldi]")
```

Description Under each category, the AREAER provides a narrative description of relevant policy announcements that became effective on specific dates within each country. As shown in Table 2, by reading the textual reports, we find the description of capital control policies documented as the follows. These entries clearly document changes in regulations or legal provisions, often citing the official titles of laws or decrees issued by central banks or foreign exchange authorities.

We use this rich textual information as the basis for extracting detailed capital control interventions. For each event, we identify key attributes such as the type of action taken, its intensity, policy direction (e.g. liberalizing or tightening), administrative level (e.g., national or sub-national), and whether the measure is related to trade or national security sanctions.[7]

Table 2. Examples of Capital Control Policy Descriptions with Status

Date	Country	Category	Description	Status
01/01/2014	Germany	Provisions specific to commercial banks and other credit institutions	Regulation (EU) No. 575/2013 on Prudential Requirements for Credit Institutions and Investment Firms introduced measures that may affect cross-border operations and capital adequacy within the EU banking framework.	yes
02/07/2013	China	Repatriation requirements	Proceeds from the issuance of shares by an overseas-listed Chinese company must be repatriated within a prescribed time and used in accordance with approved purposes.	yes
09/14/2016	United States	Inward direct investment	The sanction program that restricted certain investments related to North Korea remained in force, affecting financial transactions involving designated entities.	yes

Status The final yearly textual report includes a "status" field, which provides a binary response as "Yes/No", indicating whether the policy described in the text qualifies as a capital control and alters the country's regulatory stance in the

[7]We provide additional details on the prompt-based methodology and the structure of the resulting dataset in the following Section 2.2.

corresponding category, as shown in Table 2. For example, if a liberalizing measure eliminates all restrictions in a specific category, the status is recorded as 'No'. Conversely, if a new policy reinforces existing restrictions without changing the general regime, the status remains 'Yes', consistent with the previous year. Since the content reports from AREAER do not include the exact implementation dates of policy changes, we infer the corresponding status of each measure by matching the reported changes in a given year with the final status reported in the following year's content report, the detail data processing could be refer to Figure 10 in the finetuning section.

This binary indicator plays a central role in conventional capital control indices, which typically use the final status to quantify a country's level of capital account restrictiveness. However, this approach overlooks important dynamics—such as the intensification of controls within a category—that do not alter the binary status but nevertheless reflect meaningful policy shifts. This is a key contribution of our paper: by providing an event-level dataset, we expose the granularity that conventional indices miss. In future research, this dataset could serve as the foundation for constructing more dynamic and precise capital control indices that account for both the frequency and depth of policy interventions.

2.2 Methodology

We begin by using frontier pre-trained large language models (LLMs) to extract multidimensional characteristics from the rich textual descriptions of capital control policies. Specifically, we utilize the API-based GPT-4.1 (OpenAI, 2025) model, given its strong performance in processing regulatory text, broad knowledge base, and advanced reasoning capabilities. The model is used for initial information extraction via OpenAI's API. In contrast, later Section 3 leverages finetuned, locally hosted LLMs (e.g., Meta Llama 3.1 (Grattafiori et al., 2024)) to enable more customized classification and model adaptation.

Our methodology is based on large-scale inference from unstructured policy text using GPT-4.1 (OpenAI, 2025), a proprietary model with state-of-the-art comprehension. To ensure robustness, we set the temperature level equal to 0, and cross-validate selected outputs with alternative models, including GPT-3.5, and confirm that results are qualitatively consistent across versions.

The extraction process is structured using a two-part prompt design. First, a system prompt defines the classification schema and provides detailed instructions

for mapping policy content to structured attributes (e.g., implementation level, firm targeting, policy type). Second, the unstructured textual description is submitted as the user prompt. This structure ensures consistency across documents and facilitates scalable, standardized output. Model inference is executed via OpenAI's API using multi-thread processing. To enhance reproducibility and eliminate output randomness. Extracted results are parsed and stored in structured formats (e.g., JSON or CSV) for downstream empirical analysis. All API-based calls are conducted in a secure cloud environment, with rate-limited batching to comply with OpenAI usage constraints and cost-efficiency considerations.

In the first step, we prompt the GPT-4.1 (OpenAI, 2025) model with background knowledge about the structure of the AREAER annual reports. To accomplish this, we provide the model with sample reports and instruct it to read and interpret the layout and content of each section. This step ensures that the model understands the institutional and legal context in which capital control measures are described.

At the same time, we incorporate definitions and classification standards from two complementary data sources. First, we reference the Dataset of Capital Flow Management Measures (CFMs), which defines CFMs as policy tools aimed at influencing cross-border capital movements, including both inflows and outflows (Chang et al., 2024). Second, we draw on the structure of the Global Trade Alert (GTA) dataset, which classifies state interventions using a three-tier system: the country act grouping, the state act, and the intervention. In our implementation, we focus on the country act and intervention levels, consistent with how GTA organizes and collects policy information (Evenett, 2009).

```
system_prompt = """
You are a senior policy analyst. Your job is to extract structured information
from IMF Exchange Arrangements and Exchange Restrictions (AREAER) reports.
The example of reports is as follows. And the textual report includes the
capital control policies in countries with detailedd descriptions:

{"index": "X.D.2.", "category": "Inward direct investment", "code": "172",
"status": "yes", "description": "Investments require prior approval and
are administered by the Investment Committee. The law stipulates that
foreign investment in the Islamic State of Afghanistan can take place only
through joint ventures, with foreign participation not exceeding 49%, and
that an investment approved by the Investment Committee requires no further
license in order to operate in the Islamic State of Afghanistan. The Foreign
and Domestic Private Investment Law includes the following provisions:
(1) income tax exemption for four years (six years outside Kabul province),
beginning with the date of the first sale of products resulting from the new
investment; (2) exemption from import duties on essential imports (mainly for
capital goods)}
"""
```

Once the model is able to understand the structure of the AREAER reports and recognize capital control–related categories and policy descriptions, we proceed to prompt the LLM to read individual entries and extract the following characteristics from the text. To facilitate manual verification of the assigned categories, we also instruct the model to generate a brief justification for each classification and to cite the corresponding sentence(s) from the original description. This step helps ensure the transparency and interpretability of the model's outputs, and allows researchers to audit the classification process when necessary.

```
You are a senior policy analyst. Your job is to extract structured information
from IMF capital control descriptions.
Return all results as a JSON object with specific fields. Use precise and short
terms.
If a field is not explicitly mentioned, return null or false.
For each extracted field, also include a new field called '[Field]_source_
sentence' showing the exact sentence from the original description that
supportsyour extraction.

For 'Action', classify by using the verb words for applying the policies:

- "Action": Classify the policy's primary regulatory move into one of the
following **10 fixed categories**.
Choose the most important action described in the text. If multiple actions
are present, select the one with the greatest policy impact. Return only
one of the following values:
    - prohibit: Explicitly bans a type of transaction or capital flow.
      Example: "Residents are prohibited from acquiring foreign bonds."
    - limit: Imposes a cap or threshold on volume, frequency, or eligible
    entities.
      Example: "A ceiling was placed on foreign portfolio investment."
    - suspend: Temporarily halts or freezes an activity that was previously
    allowed.
      Example: "Licensing of outward investments was suspended."
    - require approval: Allows the activity only if prior approval or
    registration is granted.
      Example: "All real estate purchases by nonresidents require prior
      approval."
    - subject to quota: Allows the activity but restricts it under a quota
    or allocation.
      Example: "Foreign exchange purchases for education are subject to quota."
    - permit: Explicitly authorizes or legalizes an activity that was
    previously restricted.
      Example: "Corporates are permitted to invest abroad in joint ventures."
    - remove: Cancels a previous restriction or approval requirement.
      Example: "The requirement for prior approval was removed."
    - ease: Makes an existing restriction more flexible (e.g., expanding
    coverage, simplifying approval).
      Example: "Approval procedures were eased for investment abroad."
    - amend: Modifies the wording or scope of existing regulation without
    clearly changing its restrictiveness.
      Example: "The regulation was amended to update procedural definitions."
    - clarify: Provides clarification or interpretation of existing rules
    without changing legal effect.
      Example: "The scope of 'resident' was clarified to include offshore
      subsidiaries."
...
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```
For 'Action Intensity', classify only into the following categories based on
meaning:
- restrictive: Used when the policy limits or prohibits cross-border
transactions.Common cues: prohibit, ban, restrict, suspend, limit, impose,
freeze.
  Example: "Residents are no longer allowed to purchase foreign securities."
- liberalizing: Used when the policy removes, relaxes, or eases controls. Cues:
allow, remove, lift, permit, ease, liberalize.
  Example: "Restrictions on nonresidents purchasing local bonds were lifted."
- conditional: Used when the policy allows actions only under specific
conditions (approval, quota, limits).
  Example: "Foreign investment is allowed, subject to approval by the
  Ministry."
- neutral: Used when the change is administrative or direction is unclear.
  Example: "The central bank clarified reporting procedures for offshore
  transactions."

For 'Action Direction', classify only as:
- inward: Affects inflows into the country.
- outward: Affects outflows from the country.
- both: Simultaneously affects inward and outward flows.
- undefined: Direction not specified or unclear.
For 'Action Level', classify only as:
- supranational: Decision made by a regional or international body (e.g., EU).
- national: Implemented by central government.
- subnational: Implemented by local or provincial authority.
- undefined: Level of authority not specified.
For 'Instrument', classify by using the policies tools (e.g., foreign exchange,
bank credit,bank reserve requirement)
For 'Actor', classify by using the policies makers (e.g., central bank,
government, commercial banks)
For 'Beneficiary', classify by using the policies aiming groups of investor
(e.g., exporters, travelers)
For 'Condition', classify by additional requirement (e.g., without approval,
only on request,subject to approval)
- without  - with  (e.g., only on request,subject to approval)
For 'Target Country', identify the country who been targeted with the policies
For 'Target Industry', identify the industry which been targeted with the
policies
For 'Is Trade Policy', return true if the measure affects trade in goods or
tariffs (e.g., includes words like import, export, quota, tariff).
For 'Is Sanction', return true if the measure involves bans, freezes, or
disallowing actions typically against countries or individuals.
For 'Is National Security', return true if the justification or mechanism
refers to security, terrorism, or national interest.
"""
```

We initially store the model outputs in JSON format and subsequently convert them into CSV files upon completion of the LLM processing. After extracting relevant information from each policy description in the AREAER, we match the resulting records with metadata including the policy date, country name, status, and categorical identifiers such as geographic region, income level, and sub-income classification.

2.3 Capital Control Measures Dataset: Stylized Facts

The structure of the Capital Control Measures (CCM) dataset is summarized in Table 3. Each observation represents a capital control policy intervention at the daily level, classified across a rich set of dimensions. In addition to basic identifiers such as the date of implementation, reporting country, and full policy description, each entry is aligned with the hierarchical IMF AREAER classification system through a category index and category name.

Our CCM dataset captures a wide array of characteristics for each policy event, including the type of action (e.g., prohibit, permit), its intensity (restrictive, conditional, liberalizing), direction (inward, outward, or both), and jurisdictional level (national, subnational, or supranational). It further records contextual details such as the instrument used, the implementing authority, affected sectors or entities, and whether the policy relates to trade, sanctions, or national security. To ensure interpretability, each entry also includes the original IMF AREAER status (Yes/No) and a justification generated by a large language model, citing relevant text and reasoning.

In summary, the CCM dataset covers 45 types of categorized capital control interventions across 196 countries from 1999 to 2023.[8] It provides event-level information at a daily frequency on policy actions implemented globally to regulate cross-border capital flows. Figure 3 presents the geographic distribution of capital control measures across different world regions. The dataset captures policy interventions from nearly all countries covered by the IMF AREAER, offering broad global coverage. In total, the dataset includes 5,198 documented intervention events.

[8] In the finetuning section (Section 3), the training dataset covers data only up to 2022, as the final AREAER report for each year is required to determine the status conditions. The AREAER report for 2023 has not yet been released as of the time of writing.

Table 3. Structure of the Capital Control Measures Dataset

Field	**Description**
Year	The implemented year of the capital control policies
IFS code	Country code
Country	Name of the reporting country
Region	Region of the reporting country
Income group	Income group of the reporting country based on World Bank
Income subgroup	Income subgroup of the reporting country based on World Bank
Index Code	Index code provided by IMF
Category Index	Hierarchical index consistent with IMF AREAER classification
Category	Name of the capital control category (e.g., XI.A.2.a.1.i)
Date	Effective date of the intervention
Description	Full text description of the capital control measure
Date of Retroactive Changes	The date if there is a date for canceling this policy (if applicable)
Action	Verbs describing the measure (e.g., prohibit, permit, require approval)
Action Intensity	Restrictive / Conditional / Liberalizing / Neutral
Action Direction	Inward / Outward / Both / Undefined
Action Level	Supranational / National / Subnational / Undefined
Instrument	Policy tool involved (e.g., foreign exchange, credit, reserve requirement)
Actor	Entity implementing the policy (e.g., central bank, government)
Condition	With (e.g., subject to approval) / Without (e.g., no approval required)
Beneficiary	Group intended to benefit or be affected (e.g., exporters, travelers)
Target Country	Country explicitly targeted by the measure (if applicable)
Target Industry	Sector targeted by the policy (if applicable)
Target Industry	Sector targeted by the policy (if applicable)
Limit/Threshold	Limits number or threshold of the policy (if applicable)
Is Trade Policy	True if measure relates to trade in goods or tariffs
Is Sanction	True if measure involves bans, freezes, or restricted parties
Is National Security	True if measure references security or national interest
LLM Reasoning	Cited phrase and rationale reasoning extracted by LLMs

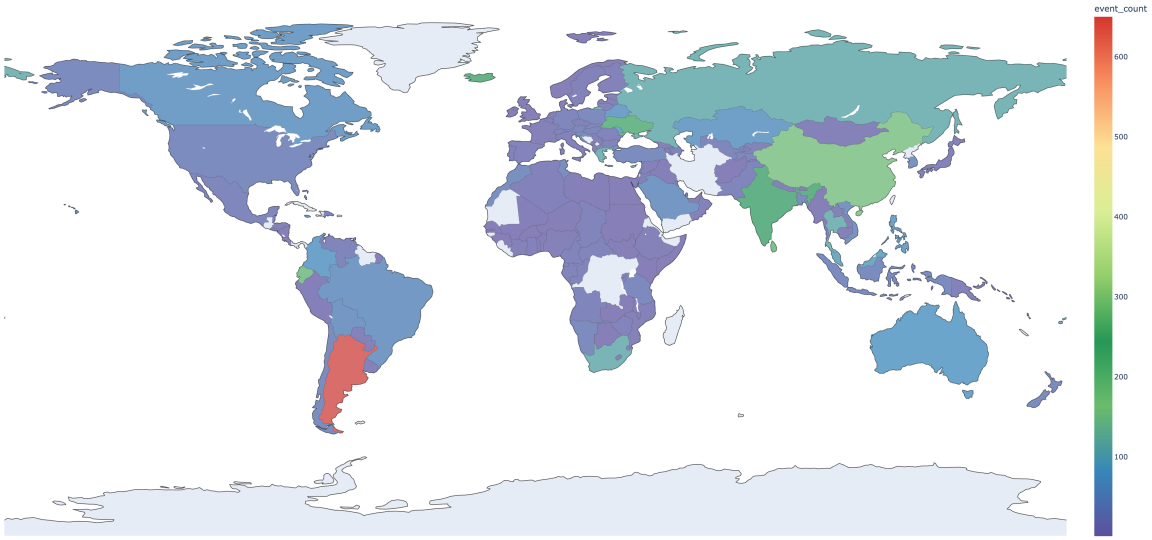


Figure 3. Total Capital Control Measures Distribution Map

In addition, the CCM dataset covers 45 types of capital control measures across key sectors, shown in Figure 4. It includes the capital market, money market, credit operations, derivatives, direct investment, and real estate. Aligned with the classification framework used by Fernandez et al. (2016), we also provide the measures matched with detailed subcategories such as "Purchase locally by nonresidents" and "Sale or issue abroad by residents." This level of granularity enables us to infer the directional nature of each measure—whether it targets capital inflows, outflows, or both—based on the specific transaction regulated, and allows us to provide the action direction field in the CCM dataset.

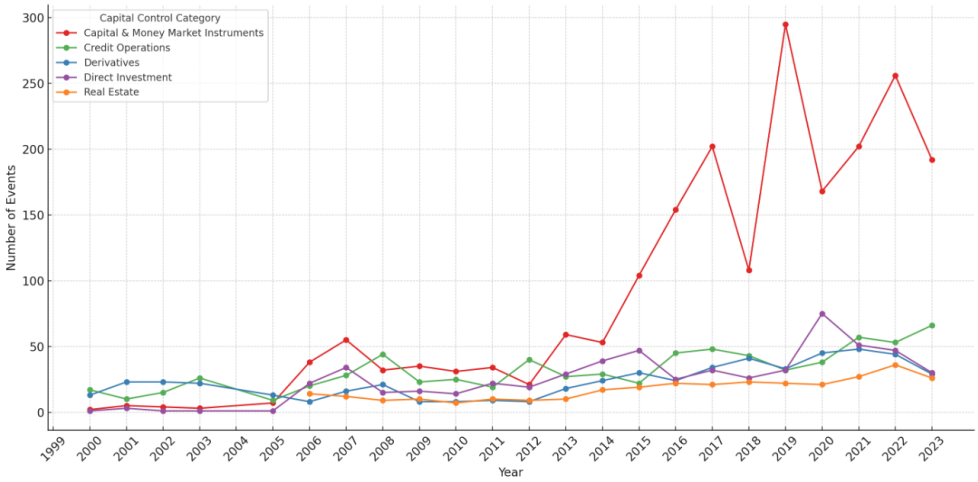


Figure 4. Total Capital Control Measures Distribution by Category

As shown in Figure 4, most capital control interventions have been implemented in the capital and money market instruments sectors. This pattern is consistent with stylized facts in the literature, which suggest that these sectors are often the first to be targeted by governments during episodes of financial stress.

Notably, Figure 4, shows that the frequency of capital control measures increased sharply around the time of the global financial crisis. Using the event-level CCM dataset, we observe a clear upward trend beginning as early as late 2005, with a steady rise in intervention activity across multiple categories leading up to 2008. A similar pattern emerges around the period of quantitative easing (QE) withdrawal in 2012, when a noticeable increase in capital control announcements followed the Fed's signaling of QE exit. Similary, from the dataset, we could also observe the increasing capital intervention events during and after the COVID-19 pandemic. These dynamics underscore the value of event-level data in capturing both anticipatory and reactive capital control measures during periods of financial volatility.

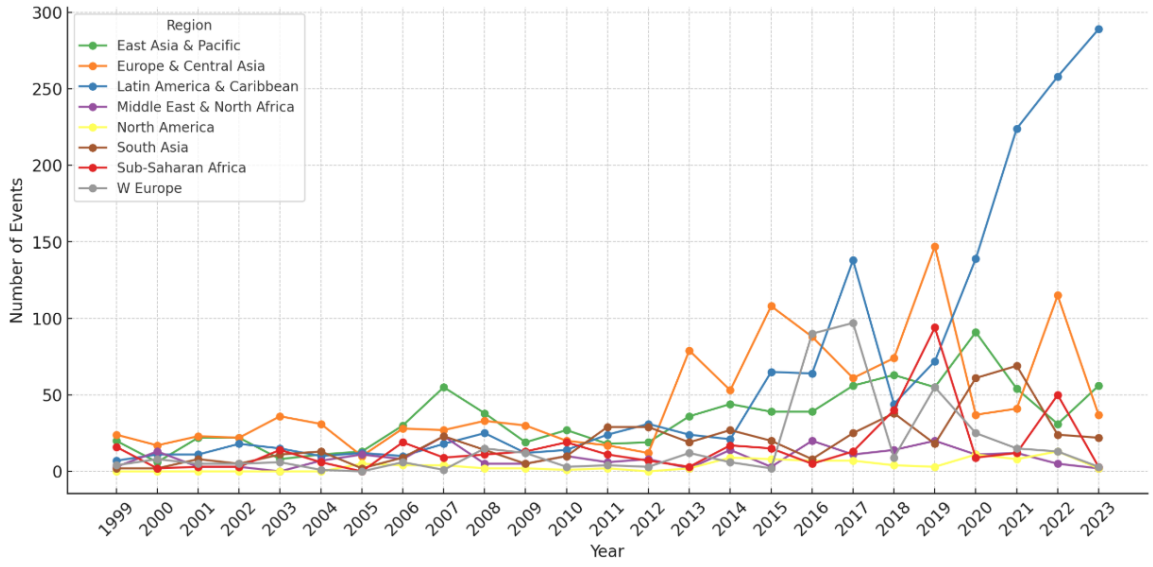


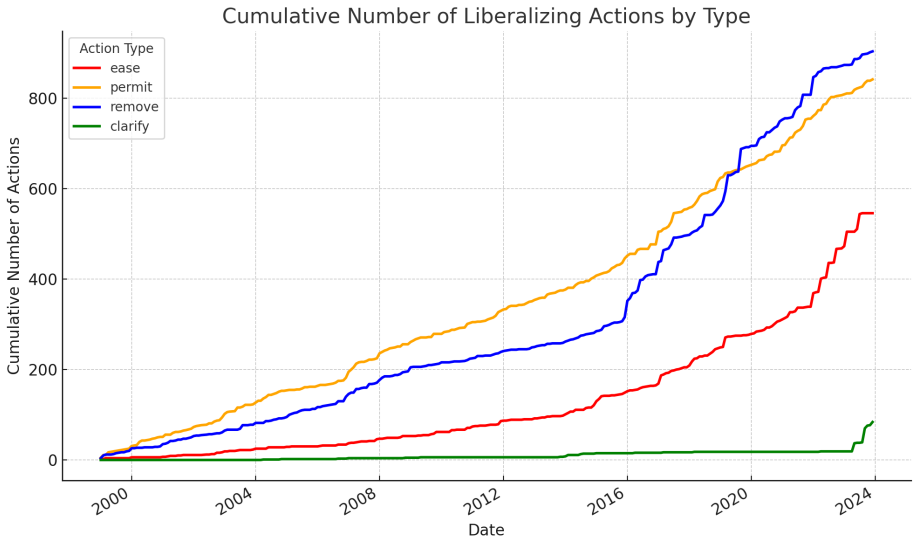
Figure 5. Total Capital Control Measures Distribution by Regions

In addition to differences by policy category, we also observe substantial regional variation in capital control activity, as shown in Figure 5. The figure displays the time-series evolution of total capital control measures across eight major world regions.

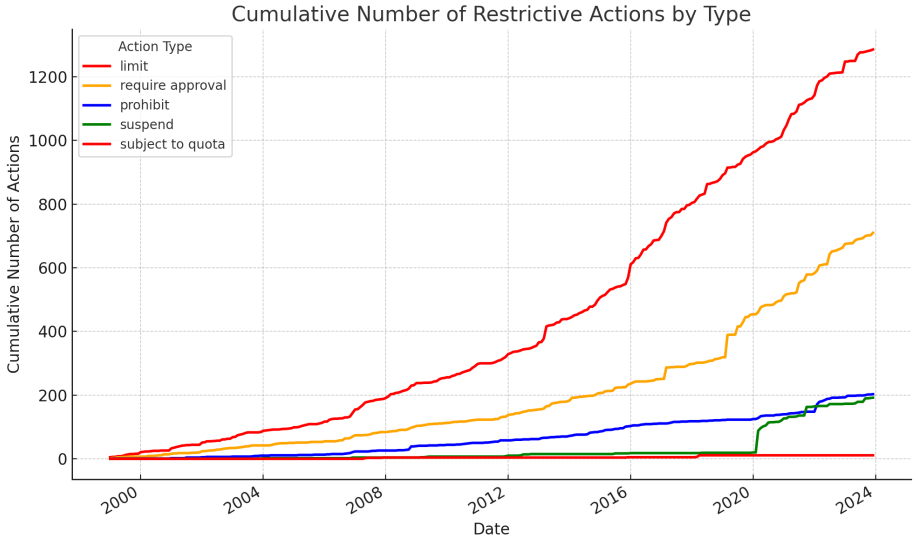
The data indicate that East Asia and Pacific countries responded most actively

to the 2008 global financial crisis, while European countries exhibited heightened sensitivity to the monetary tightening associated with the exit from quantitative easing (QE) policies. Notably, capital control activity in Latin America spiked sharply following the COVID-19 outbreak, reaching a record high of approximately 300 interventions in 2023—the largest number of events recorded in a single year for any region.

Not only the stylized facts based on the ground-level distribution, we also add more dimensional characteristics based on the rich textual analysis. As we discussed above about the prompting process and the field setup, our dataset introduces a new field by reading the descriptions of each measure and extracting the "action types". The action types help researchers further distinguish the policies with clearer action labels, such as ease, permit, prohibit, or suspend. We provide nine categories of action types, which can be broadly classified into two larger groups: *Liberalizing Actions* and *Restrictive Actions*. The cumulative frequency of these two types of actions is plotted in Figure 6.



a. Liberalizing Actions



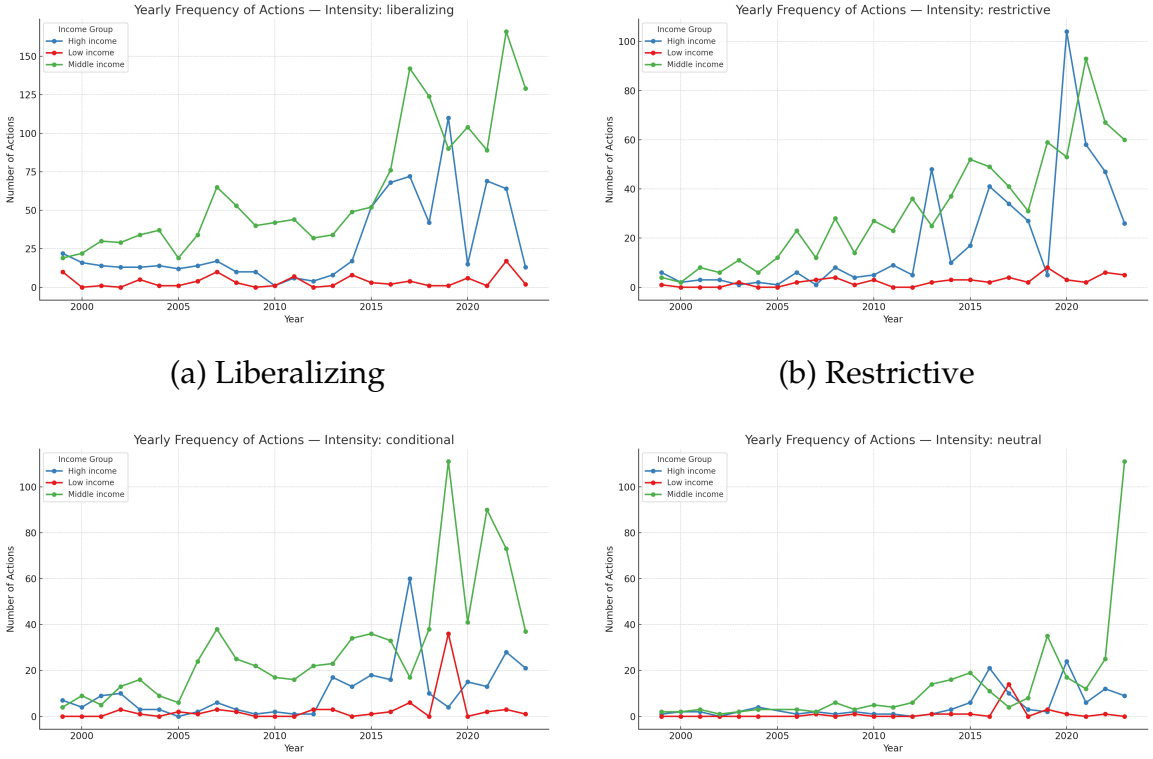
b. Restrictive Actions

Figure 6. Cumulative CCM by Action Types

Overall, the number of restrictive actions across all action types is higher than that of liberalizing actions. Within the liberalizing group, as shown in Figure 6 part A, "permit" actions appear most frequently, followed by "remove" and "ease" announcements. Beyond the overall trend, it is notable that "remove" actions began increasing more rapidly after 2016 and surpassed "permit" actions around 2020. The number of "ease" actions also spiked following the COVID-19 outbreak, consistent with the notion that governments adopted looser capital control measures

to support economic recovery during the post-COVID period. In comparison, Figure 6 part B shows that among restrictive measures, "limit" actions consistently outnumber all other types. Similarly, the number of "suspend" actions rose noticeably during the COVID-19 period, indicating tightening in response to heightened uncertainty.

We also classify the action intensity into four types: liberalizing, restrictive, conditional, and neutral. The detailed explanation of how we define and assign these categories is provided in Section 2.2. To help the pre-trained LLM understand our classification goals, we provided it with the definitions of each category, along with examples for each type, so that the model had clear references and could better follow our intended classification logic.



(a) Liberalizing

(b) Restrictive

(c) Conditional

(d) Neutral

Figure 7. CCM by Action Intensity and Income Group

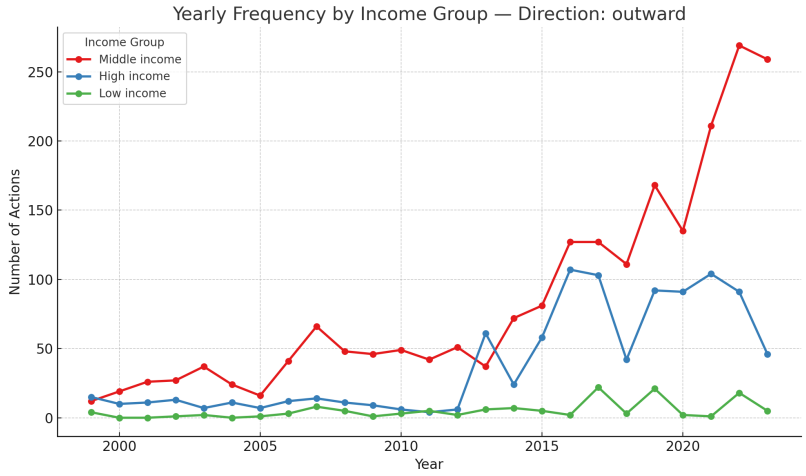
Figure 7 presents the distribution of capital control measures by income group and action intensity. The four sub-panels show that middle-income countries are, overall, the most frequent users of capital control interventions. A closer look reveals that these countries issued a significant number of liberalizing and condi-

tional measures in the years leading up to the 2008 financial crisis. However, the frequency of such interventions declined sharply during and after the crisis period.

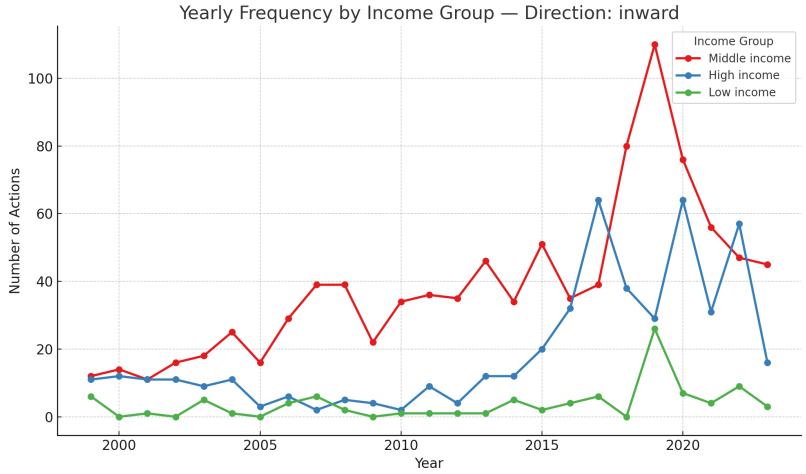
A noteworthy pattern revealed by the action intensity data is that high-income countries tend to lead the trends compared to middle- and low-income groups across all types of capital control actions. This suggests the presence of potential spillover effects, whereby policy shifts in advanced economies may influence the behavior of lower-income countries. The underlying story is that when high-income countries adopt a particular type of capital control, whether imposing restrictions in response to global financial stress or liberalizing to attract capital inflows, other countries often follow with similar interventions shortly thereafter. This pattern may reflect a mix of market contagion, peer effects, and policy learning, as policymakers in emerging and developing economies respond to signals from larger financial centers. While we do not explore this dynamic in detail here, it presents a promising avenue for future research that could investigate the timing, channels, and asymmetry of such cross-country policy transmission.

Beyond category-level information that indicates policy directions, the CCM dataset also leverages the textual descriptions in AREAER reports to classify whether each capital control measure targets inflows or outflows. This textual approach provides more robust and interpretable reasoning behind the classification, compared to relying solely on the IMF-assigned categories [9] The figure 8 is one of the time-series distribution using the *Action Direction* field from the CCM dataset.

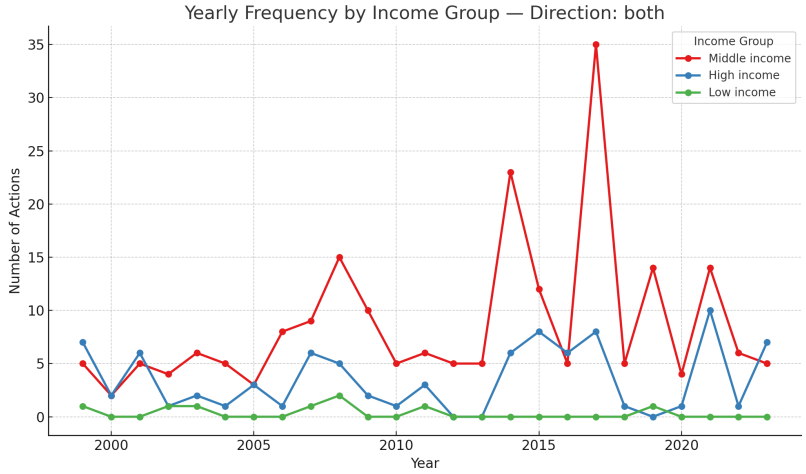
[9]During the data cleaning process, we found that many policy entries fall under broad category labels that lack clear information about whether they apply to capital inflows or outflows. As noted in the technical appendix of Fernández et al. (citation), assigning a specific direction often requires manual labeling to match the deepest level of the IMF's classification. This challenge is one of the key motivations for developing our finetuned LLM, described in Section 3, which enables automated classification into fine-grained categories using our self-trained open-source *CCM-Llama* 3.1 model.



a. Outward Direction



b. Inward Direction



c. Both

Figure 8. CCM by Action Directions

In the example shown in the figure above, we continue to classify countries by income level, dividing them into high-, middle-, and low-income groups. It is clear that middle-income countries implemented more outward-related capital control measures than other types of directional actions, and also more than other country groups. By examining these patterns, we can compare how countries responded to the COVID-19 pandemic: in order to prevent capital outflows and manage financial disruptions caused by the crisis, middle-income countries tended to adopt more outward-targeted capital control policies, rather than focusing on inflow restrictions. This is a preliminary observation based purely on the total number of capital control measures. However, with the CCM dataset, we can locate any specific country and category, allowing for deeper analysis of policy performance or reactions in greater detail in future work.

In summary, the CCM dataset captures rich variation in capital control interventions by extracting structured information through LLMs. In this section, we have presented several stylized facts to illustrate the dataset's advantages and provide a broader sense of its potential uses. Looking ahead, this event-level dataset offers many possibilities for further research across different policy contexts.As an example, in section 4, we conduct a simple empirical analysis using the CCM dataset to implement an event study examining the impact of capital control measures on global fund flows.

3 Classifying Capital Control Categories with Finetuned LLM

In addition to introducing the Capital Control Measures (CCM) dataset, which captures the multidimensional characteristics of each capital intervention policy from the AREAER reports, we further develop an automated categorization process that eliminates human labeling process and is adaptable to multiple data sources. To facilitate the classification of capital control measures and the determination of status conditions for each CCM event, we finetune an open-source large language model based on Meta Llama 3.1 (Grattafiori et al., 2024), which we named *CCM-Llama*. This model is trained to automatically classify the textual descriptions of capital control measures into the predefined IMF AREAER categories, along with their corresponding status outcomes.

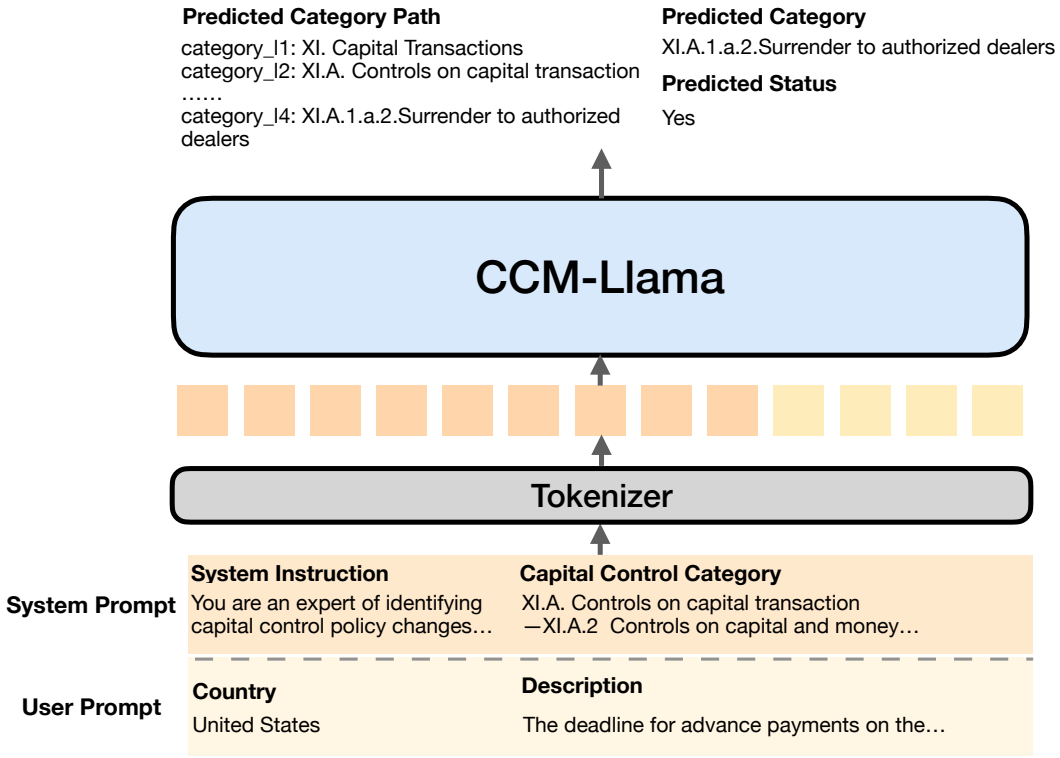


Figure 9. The Inference Process of *CCM-Llama*

Notes: The model is prompted to classify the description of capital control into IMF AREAER final report categories.

3.1 Method Overview

As shown in figure 9, our goal is to finetune LLMs to understand capital control policy texts and accurately classify them into the relevant categories and statuses defined by the IMF AREAER.

Specifically, the finetuned LLM is prompted with classification instructions, along with the country name and the textual description of the policy. The input is tokenized into individual tokens to allow for model processing. The model then encodes the tokenized input and outputs the predicted category corresponding to the IMF AREAER.

We design a rigorous three-step pipeline to construct our dataset to enable the finetuning process based on the existing IMF AREAER sources: the final report and the yearly changes. By aligning each policy text with its corresponding category and resulting status, we build a comprehensive training dataset. In total, we collect 29,012 examples covering 196 countries from 1999 to 2022.

With the collected dataset, we finetune the state-of-the-art Meta LlaMA 3.1-8B (Grattafiori et al., 2024) model to make it further understand the relationship between the capital control policy description and category. During finetuning, we apply a standard language modeling approach (Zhao et al., 2023), training the model to predict the next word in a sequence based on its preceding context. This enables the model to learn how to interpret nuanced policy descriptions and classify them according to IMF-defined categories and status labels. Through this combination of domain-specific data and advanced language modeling, we develop a robust system for automated policy classification. The remainder of this section details our dataset construction steps and finetuning methodology.

3.2 Finetuning Dataset Construction

Our dataset is based on the IMF AREAER final report and yearly changes. As introduced in Section 2.1, the AREAER report provides each country's detailed status of each IMF category, while the yearly changes give the published textual policy description and its corresponding changes to a specific IMF category each year. By combining these two sources, we could extract the input and the ground-truth answer for our training dataset.

Each input consists of: (1) the textual description of a capital control policy, and 2) the name of the country implementing the policy. We introduce the country

information to allow the model to draw on relevant background knowledge stored in its pretrained parameters, which could help disambiguate context-dependent classifications. On the other hand, the ground-truth answer consists of: (1) the IMF category to which the text corresponds, and (2) the resulting status of such category as affected by the described capital control policy.

To robustly construct the inputs and ground-truth labels described above, we design a three-step framework for building our training dataset: (1) Country Deduplication and Data Merging, (2) Training Pair Construction, and (3) Format Transformation. The overall data collection process is illustrated in Figure 10.

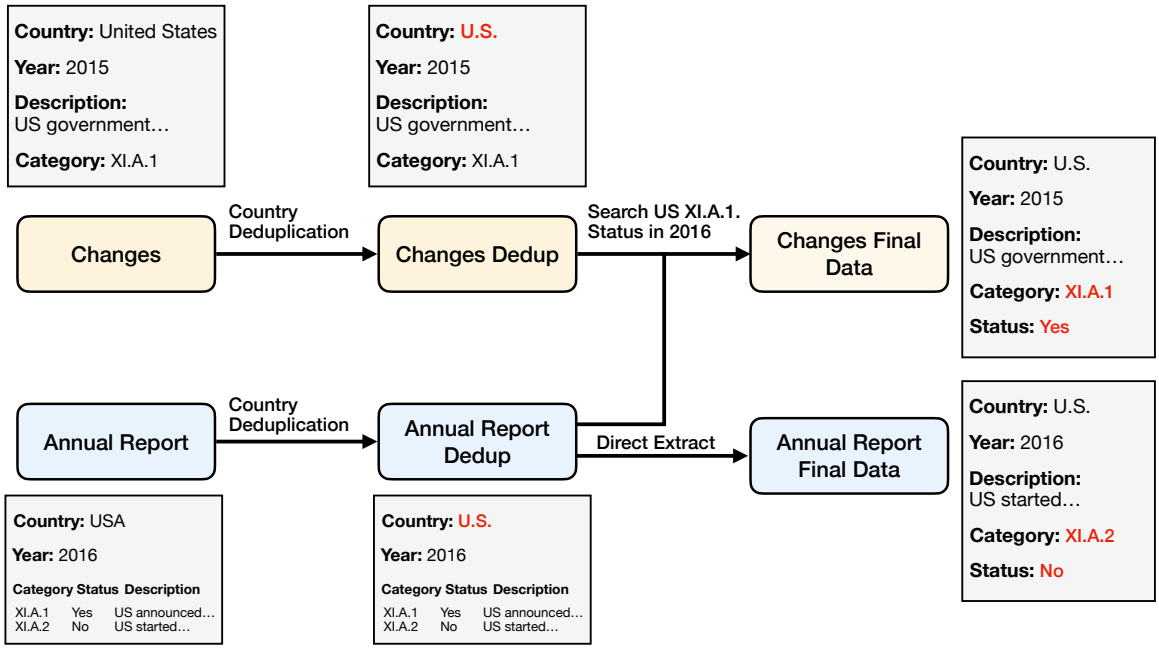


Figure 10. Demonstration of Finetuning Data Collection Process

Step 1: Country Deduplication and Data Merging By examining the original report, we identify that some countries in the dataset have multiple representations (e.g., "Hong Kong" and "Hong Kong SAR"), which affects country-level data aggregation. To address this, we first utilize GPT-4o to analyze the unique country names and generate a mapping that merges equivalent representations. A meticulous human review is then conducted to validate the accuracy of GPT-4o's mapping. The detailed mappings are presented in Table A2. With the standardized country names, we merged all the data from 1999 to 2022 and then grouped them by country for both the final report and yearly changes.

Step 2: Training Pair Construction At this stage, we transform the merged datasets into the desired input and ground-truth format. Through careful examination, we identify two types of data that can be used to form training pairs.

The first type is directly derived from the final report. As shown in the lower section of Figure 10, for each country in a given year, we collect the textual description of a given IMF category and the country as the input. The corresponding ground-truth answer consists of the category label and its status. This provides naturally aligned input and ground-truth answer pairs.

The second type of data requires the combination of information from both the final report and yearly changes. The process is demonstrated in the upper section of Figure 10. For a given policy change recorded in the yearly changes for a country n in year y, we identify the affected category in the yearly changes. Since the final resulting status is not explicitly written in the yearly changes, we then retrieve the status of the affected category from the final report for country n in year $y+1$ and regard it as the status caused by the policy change. We then record the input as the policy change with the country information and the ground-truth as the affected category and the final status at year $y+1$. By iterating over all such policy changes, we build a comprehensive and temporally aligned training dataset.

Step 3: Format Transformation Since finetuning LLMs requires data to follow the chat completion format[10]—which includes a system message, a user message, and an assistant message—we perform a format transformation step to adapt our training data accordingly. This step also allows us to incorporate additional background context to help the LLM better understand the task. An exemplar case is shown in Table 4.

Specifically, we craft a detailed system message to provide the LLM with domain knowledge and task-specific instructions. This message includes all relevant category options related to capital controls, and provides: (1) the hierarchical structure of the categories based on IMF AREAER final report, and (2) a concise one-sentence description for each category. The detailed hierarchy and description are shown in Table A1 in Appendix A. This enriched context helps the LLM more accurately understand both the domain and the classification choices (Liu et

[10]https://platform.openai.com/docs/guides/text?api-mode=chat

Table 4. Exemplar Chat Format for Finetuning Dataset

Message	Content
System	You are an expert in identifying the capital policy change and updating the IMF category status based on the input text. Please select from outer layer to the inner layer. Please consider both the country's capital control status and background and the given text. Here are the hierarchical structures for the category with its description: **XI.A.** Controls on capital transactions — Restrictions on cross-border capital flows, covering investment, credit, and real estate transactions. - **XI.A.2.** Controls on capital and money market instruments — Rules regulating international transactions in equity, debt, money markets, and investment funds. - **XI.A.2.a.** On capital market securities — Measures on shares and bonds issued or acquired by residents or nonresidents. ... (truncated for brevity)
User	**Country:** United States **Policy change:** Executive Order 13722, *Blocking Property of the Government of North Korea and the Workers' Party of Korea and Prohibiting Certain Transactions with respect to the Democratic People's Republic of Korea*, was issued.
Assistant	`{"category_path": {"category_l1": "XI.Capital Transactions", "category_l2": "XI.A.Controls on capital transactions", "category_l3": "XI.A.5.Controls on direct investment", "target_category": "XI.A.5.b.Inward direct investment"}, "index": "XI.A.5.b.", "category": "Inward direct investment", "status": "yes"}`

al., 2024). The user message, which serves as the query in the chat format, includes the country and the policy change text. The assistant message, representing the LLM's expected response, follows a structured reasoning schema. The outputs of the assistant message contains: (1) the reasoning path leading to the final answer, guided by the category hierarchy defined in the system message; (2) the inferred change category; (3) the updated status.

In addition, to make sure the model could distinguish capital control measures from unrelated policy measures, we also include the non-capital-control sections of the final report and yearly changes into the training dataset, with the same data

collection and formatting procedure applied.

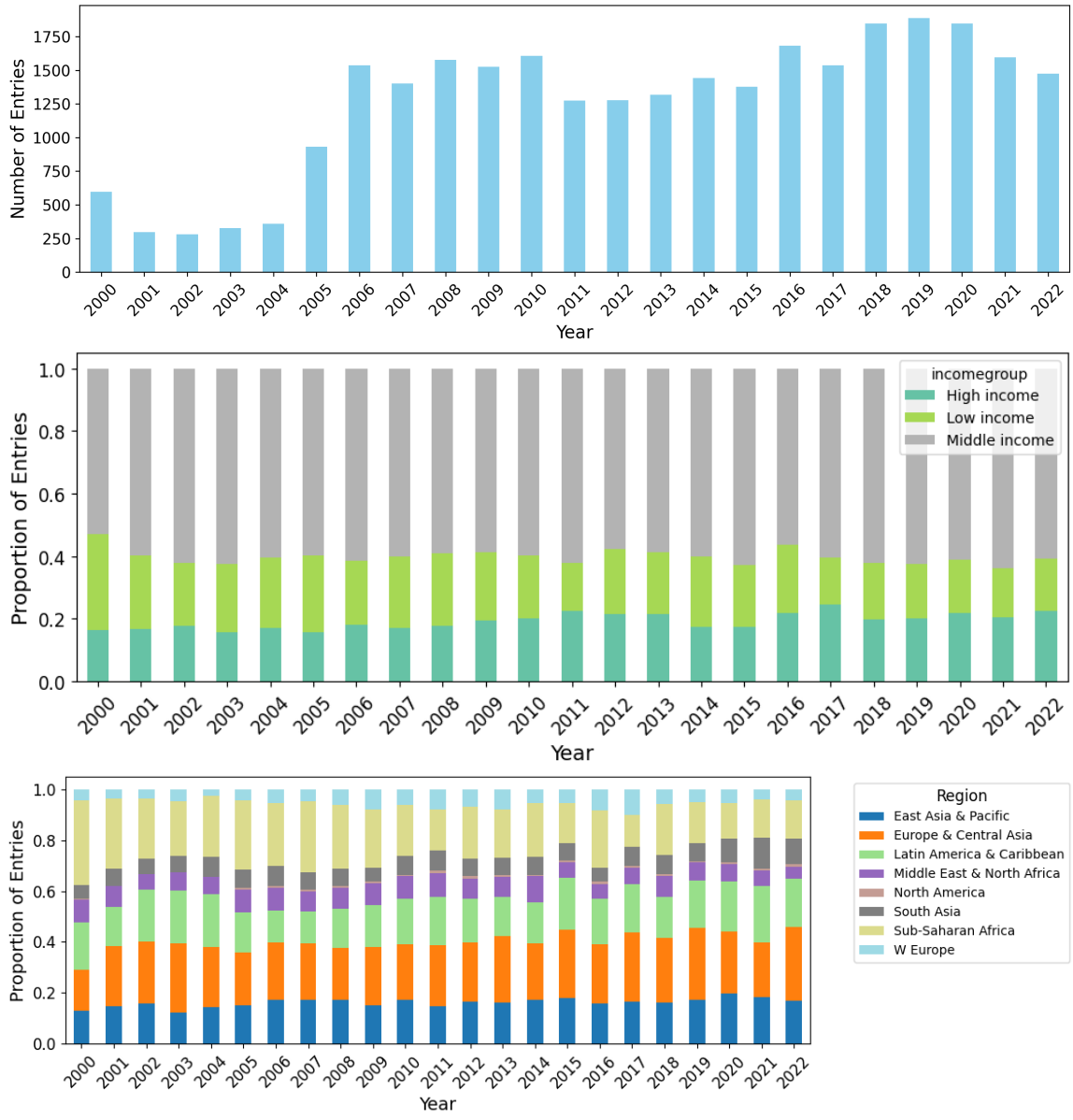


Figure 11. Distribution of Our Finetuning Dataset

Top: Data distribution by year; Middle: Data distribution by income group; Bottom: Data distribution by region

Finetuning-Dataset Descriptions In total, our dataset consists of 29,012 examples spanning 196 countries from 1999 to 2022. In detail, 14,182 examples fall within capital control categories, while the remaining 14,830 belong to other policy

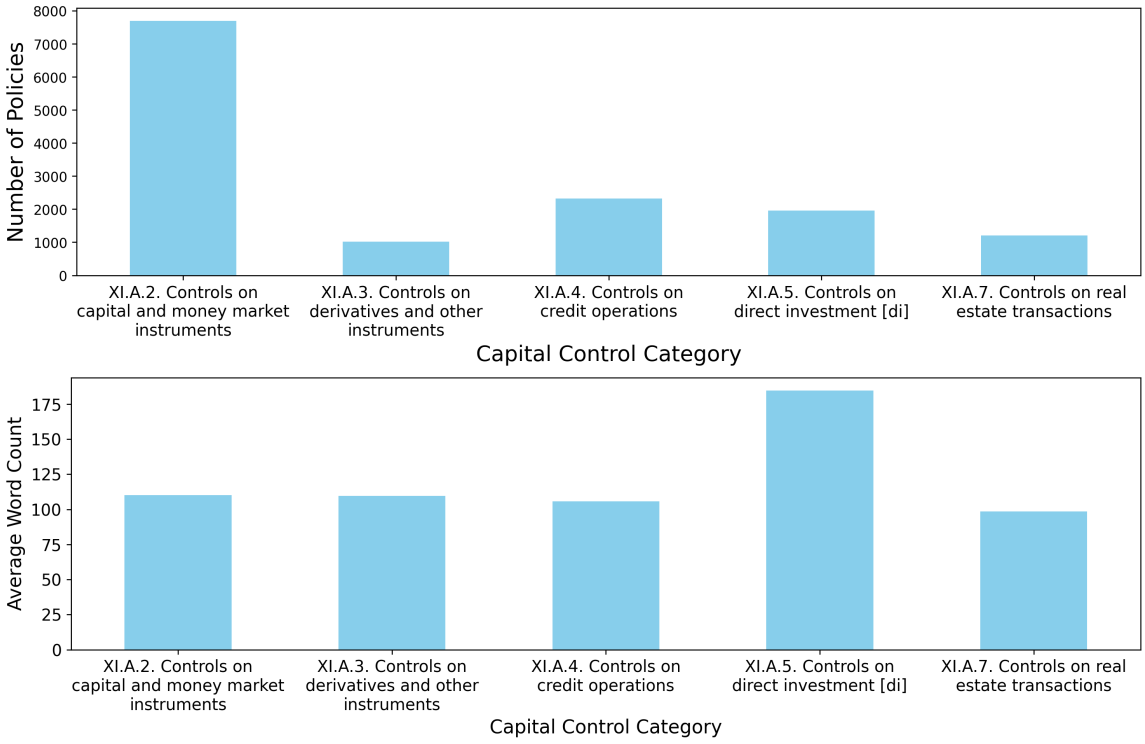


Figure 12. Distribution of Capital Control Data

Top: Distribution of Capital Control Data by Category; Bottom: The Average Word Count of Each Category.

categories. This balanced distributions cross the related categories and unrelated ones enhance our model to have the capability of learning distinguishment effectively.

Additionally, we analyze the dataset distribution by year, income group, and region. As shown in Figure 11, our dataset covers all income groups and regions. We ensure a balanced representation across years and groups to better support effective model learning. Finally, we closely examine the capital control policy data. As presented in Figure 12, our dataset includes examples from every capital control category defined by the IMF. Moreover, the average text length exceeds 100 words, ensuring that each policy description provides sufficient contextual information for accurate classification.

3.3 Model Finetuning Process

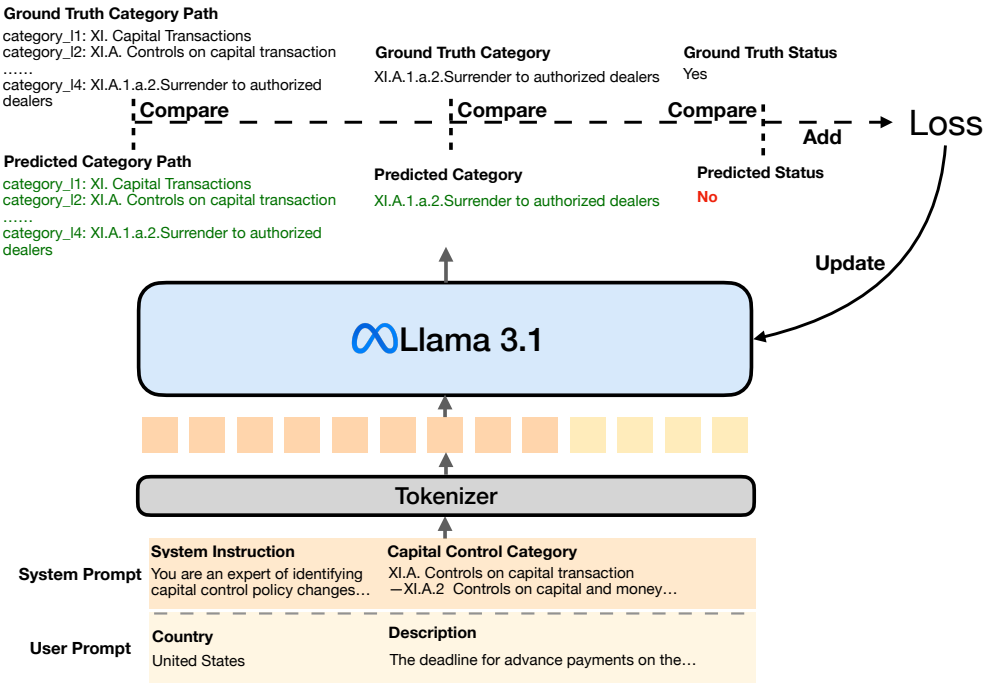


Figure 13. The Model Finetuning Process

Implementation Details We split our dataset of 29,012 examples into training, validation, and test sets following a standardized procedure. The training set contains 28,412 examples, while the validation and test sets contain 100 and 500 examples, respectively. Model training is conducted on two NVIDIA A6000 GPUs. We use a learning rate of 1×10^{-5} with a linear decay schedule, a batch size of 1, and evaluate the model every 200 training steps using the validation set. The final model is selected based on its best performance on the validation data. Training is run for a total of 2 epochs.

We leverage Meta's LLaMA 3.1 (Grattafiori et al., 2024) as our pretrained base model due to its extensive training on diverse and high-quality textual corpora, including substantial content from economics and finance domains. This broad coverage provides a strong foundation for downstream adaptation. We initialize our model using the official checkpoint available via Hugging Face[11] and finetune the entire model to maximize its adaptability to our specific task.

Finetuning Objective Our finetuning procedure follows the standard language modeling paradigm. For each data point we obtain from Section 3.2, we first

[11] https://huggingface.co/meta-llama/Llama-3.1-8B

use the model's tokenizer to break the full text into a sequence of tokens $t = (t_1, t_2, \ldots, t_n)$. Then the model is trained to predict the next token at each position. Specifically, at position i, the model receives the prefix sequence $(t_1, \ldots, t_{i-1})$ as input and learns to predict the token t_i. The training objective minimizes the negative log-likelihood loss over the entire sequence:

$$\mathcal{L}_{\text{LM}} = -\sum_{i=1}^{n} \log P_\theta(t_i \mid t_1, \ldots, t_{i-1}), \tag{1}$$

where P_θ denotes the probability distribution over the vocabulary parameterized by the model weights θ. This autoregressive loss encourages the model to generate coherent and contextually appropriate text by learning the conditional distributions of tokens within the training corpus. The finetuning process is shown in Figure 13.

3.4 Finetuning Experiment Result

To evaluate the effectiveness of our finetuned model, we conduct comprehensive performance comparisons between our finetuned *CCM-Llama* and a range of state-of-the-art commercial and open-source language models.

Baseline Models We compare *CCM-Llama* against leading foundation models from both commercial providers and the open-source community. For commercial models, we include OpenAI GPT-4o (OpenAI, 2024) and GPT-4.1 (OpenAI, 2025), which represent the current state-of-the-art. For open-source models, we evaluate against Meta LLaMA 3.1-8B (Grattafiori et al., 2024), enabling a direct comparison with our finetuned counterpart.

Benchmark Dataset Our experiment is conducted on the test split of our dataset which contains 500 examples. The dataset contains 234 capital control-related policies and 266 non-capital control policies.

Evaluation Metrics We evaluate our model based on two key questions: (1) Can the model accurately distinguish between capital control and non-capital control policies? (2) For policies identified as capital controls, can the model correctly classify them into the appropriate sub-category?

Table 5. Experiment results for capital control binary and hierarchical classification

Binary Acc *represents binary accuracy, while* ***Hierarchical Acc*** *represents accuracy at each hierarchy level.* Δ ***over Best Baseline*** *indicates the percentage point improvement of CCM-Llama over the best-performed baseline model.*

Model	**Binary Acc**	**Hierarchical Acc**				
		L3	**L4**	**L5**	**L6**	**Avg**
Llama 3.1-8B	90.67	84.00	59.05	44.68	26.42	53.54
GPT-4o	76.07	70.09	59.63	42.07	40.74	53.13
GPT-4.1	94.44	82.91	68.81	56.55	48.15	64.10
CCM-Llama	**99.55**	**90.09**	**75.85**	**65.19**	**60.78**	**72.98**
Δ over Best Baseline	**+5.11**	**+7.18**	**+7.04**	**+8.64**	**+12.63**	**+8.88**

To address the first question, we compute the binary classification accuracy, defined as:

$$\text{Accuracy}_{\text{binary}} = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}(y_i = \hat{y}_i) \tag{2}$$

where $y_i \in \{0, 1\}$ is the ground-truth label (1 for capital control, 0 for non-capital control), $\hat{y}_i$ is the model's prediction, N is the total number of samples, and $\mathbb{I}(\cdot)$ is the indicator function that returns 1 if the argument is true and 0 otherwise.

To evaluate the second question, we compute hierarchical accuracy across six levels of the classification hierarchy (denoted as L1 through L6). Each category is represented by a hierarchical index (e.g., `XI.A.2.a.1.ii`), which we decompose into up to six levels using dot-separated components.

For each policy where the ground-truth is a capital control policy, we compare its predicted index to the ground-truth index level by level. A match at level L_k is counted only if *all previous levels* (1 to $k-1$) also match. Once a mismatch occurs at any level, deeper levels are not counted as matches. This enforces a strict top-down matching structure.

Formally, for each level $L_k \in \{1, 2, \ldots, 6\}$, we define:

$$\text{Accuracy}_{L_k} = \frac{\text{\# predictions where levels 1 through } k \text{ match}}{\text{\# instances with valid ground truth at level } k} \tag{3}$$

Results and Analysis As shown in Table 5, *CCM-Llama* achieves the highest binary classification accuracy at **99.55%**, substantially outperforming all the baseline models. This demonstrates that our model is highly reliable at identifying whether a given policy falls under the category of capital controls.

For the hierarchical accuracy evaluation, since capital control categories all start with `XI.A`, we report the accuracy from L3 to L6. In general, performance degrades with deeper levels, reflecting the increasing difficulty of fine-grained classification. Nevertheless, *CCM-Llama* consistently outperforms all baselines at each level. Especially at more fine-grained levels, L5 and L6, *CCM-Llama* maintains strong performance with more than 60% accuracy while other models drop more steeply down to less than 50%.

Overall, *CCM-Llama* achieves the highest per-layer accuracy, reaching up to **90.09%**, and an average sub-category accuracy of **72.98%** across levels L3 to L6. These results significantly outperform the best baseline model by up to 12.63%. This demonstrates the effectiveness of our domain-specific finetuning approach for structured policy classification tasks, especially in capturing subtle and complex hierarchical distinctions.

Discussion The results underscore the limitations of general-purpose LLMs, even state-of-the-art commercial models, on specialized classification tasks involving capital control policy texts. Despite their scale and general reasoning capabilities, these models underperform relative to a targeted, finetuned model like *CCM-Llama*, especially in fine-grained, taxonomy-aware prediction. These findings support the case for domain adaptation when applying LLMs to high-stakes policy domains.

With its robust performance, *CCM-Llama* unlocks broad potential for the automatic real-time and multi-source detection of capital control events. Unlike prior approaches that rely solely on human beings and gathering interventions from AREAER reports, our model can be deployed across diverse text sources, including financial news corpora such as Refinitiv News Portal and Bloo-mberg News Updates, which offer richer contextual information and higher temporal granularity. This flexibility opens the door to a wide range of applications, such as near real-time monitoring of policy interventions, early-warning systems for capital flow volatility, and enhanced input for empirical macro-finance research where timely policy signals are critical.

4 Capital Control Measures on Global Fund Flow: An Empirical Analysis

One of the key advantages of the CCM dataset is its event-based structure, which allows economists to analyze the effects of specific capital control actions with high temporal precision. In this section, after constructing the dataset through prompt-based analysis of the AREAER reports, we present an empirical example that utilizes the CCM dataset to examine how different types of policy actions, along with their intensity, impact global fund flows.

4.1 Datasets

Fund Flow Dataset. Our dependent variable is constructed using the EPFR Global fund flow dataset, which provides monthly information on portfolio allocations of mutual funds, exchange-traded funds (ETFs), and other institutional investment vehicles across destination countries. The dataset covers 47 countries over the period 2008–2017 and reports, for each fund, the fraction of total assets invested in each destination market as well as total assets under management (AUM).

A direct change in country portfolio weights reflects not only active reallocations by fund managers, but also valuation effects driven by asset price movements. To separate active fund flows from passive valuation changes, we follow the accounting-based approach of Raddatz et al. (2017), combining fund-level country weights with country-level total return indices.

Let $w_{i,c,t}$ denote the end-of-period portfolio weight of fund i invested in country c at time t, and let $\text{AUM}_{i,t}$ denote total assets under management of fund i at time t. Country-level gross returns, $R_{c,t}$, are computed from MSCI country total return indices in U.S. dollars. Monthly returns are defined as

$$R_{c,t} = \frac{P_{c,t}}{P_{c,t-1}}, \tag{4}$$

where $P_{c,t}$ denotes the MSCI total return index level for country c at time t.

Fund-level country allocations are reshaped into a fund–country–month panel, excluding cash positions. Portfolio weights are expressed in fractions such that $0 \leq w_{i,c,t} \leq 1$.

Lagged country-level assets held by fund i are given by

$$\text{AUM}_{i,c,t-1} = w_{i,c,t-1} \times \text{AUM}_{i,t-1}. \tag{5}$$

Under a buy-and-hold benchmark, the counterfactual value of these holdings at time $t$which absent any active rebalancing, is

$$\widetilde{\text{AUM}}_{i,c,t} = \text{AUM}_{i,c,t-1} \times R_{c,t}. \tag{6}$$

Actual end-of-period holdings are defined as

$$\text{AUM}_{i,c,t} = w_{i,c,t} \times \text{AUM}_{i,t}. \tag{7}$$

We then construct fund–country capital flows as the difference between actual and counterfactual holdings,

$$F_{i,c,t} = \text{AUM}_{i,c,t} - \widetilde{\text{AUM}}_{i,c,t} = w_{i,c,t}\,\text{AUM}_{i,t} - w_{i,c,t-1}\,\text{AUM}_{i,t-1}\,R_{c,t}. \tag{8}$$

This measure captures active reallocations of fund across destination countries, net of valuation effects arising from asset price changes. Country-level flows are obtained by aggregating fund–country flows across all funds investing in country c at time t. To facilitate comparison across countries and over time, we further scale country-level flows by the size of lagged assets invested in each destination. Specifically, for each country c and month t, we define the scaled country-level flow as

$$F_{c,t}^{\text{scaled}} = \frac{F_{c,t}}{\text{AUM}_{c,t-1}}, \tag{9}$$

where $F_{c,t} = \sum_i F_{i,c,t}$ denotes aggregate capital flows into country c at time t, and

$$\text{AUM}_{c,t-1} = \sum_i w_{i,c,t-1}\,\text{AUM}_{i,t-1} \tag{10}$$

is the total lagged assets under management allocated to country c across all funds.

This scaling transforms flows into a percentage change relative to the existing stock of invested assets, allowing for meaningful comparisons across countries with different market sizes and fund exposures. The scaled flow measure is used as the primary dependent variable in the empirical study as shown in Figure 14

The geographic concentration of capital flows is highly uneven. The Top 10

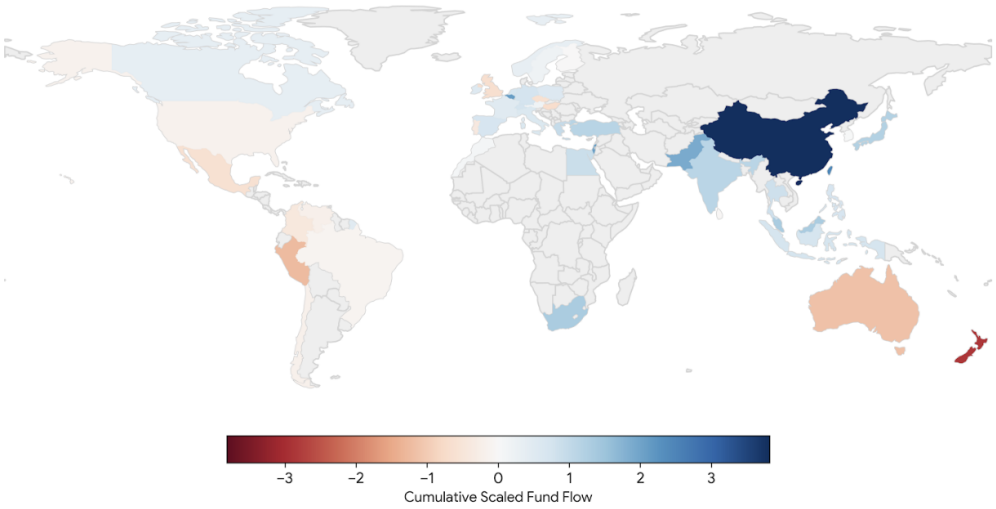


Figure 14. 1999-2016 Global Scaled Fund Flow Average Distribution

Countries with Highest Net Inflows and Outflows chart as 15 highlights the dominant recipients and sources of funds. Major developed economies like Japan, China, Germany, and France stand out as the largest beneficiaries of net capital inflows over the period. In contrast, emerging markets such as South Korea and Brazil, along with the United Kingdom and the United States, experienced significant net outflows in this specific fund flow dataset. This disparity underscores the structural imbalances in global capital allocation.

Capital Control Measures To analyze the effect of capital control measures on global fund inflows, we use the CCM dataset by focusing only on interventions classified with an "Inward" action direction. We further examine the impact of different levels of action intensity across various policy categories. These identified events serve as the basis for implementing an event study analysis on fund flow dynamics.

Control Variables Building on capital flow theory (Broner et al., 2013; Erten et al., 2021; Tille and Van Wincoop, 2010), we incorporate both global push factors and domestic pull factors as key determinants of cross-border capital movements. Global push factors capture external conditions that influence investors' decisions across countries, including global risk sentiment (measured by the VIX), U.S. interest rates, and other indicators of global financial conditions. In contrast, domestic pull factors reflect country-specific fundamentals that attract capital, such as

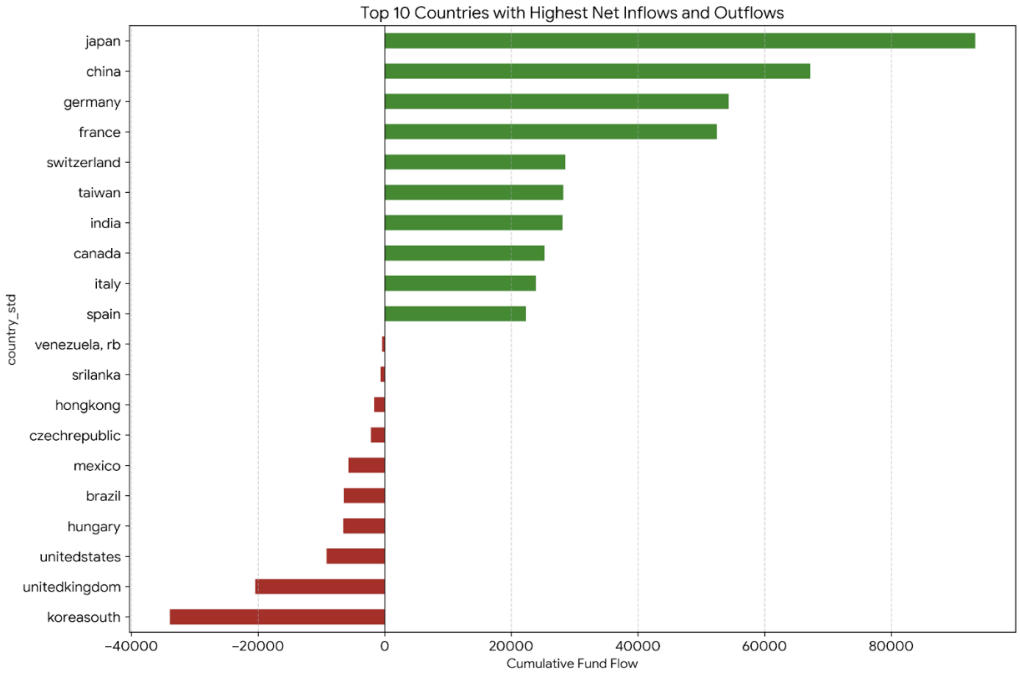


Figure 15. Top 10 Countries with Highest Net Inflows and Outflows

economic growth, financial openness, exchange rate regime, and the presence or stringency of capital control policies. These drivers have been widely emphasized in the literature on capital flows, including foundational work by Reinhart et al. (1993) and more recent contributions by Ahmed and Zlate (2014).

4.2 Empirical Method and Results

Event Study We first conduct an event study using the full sample of 34 matched countries to examine whether *inward* capital control measures affect cross-border fund inflows. Using monthly fund-level data, we evaluate the dynamic responses of fund flows around policy intervention dates, distinguishing events by their *action intensity*—namely, *liberalizing* versus *restrictive and conditional* measures.

We classify capital control events into *Liberalizing* (easing of controls) and *Restrictive* (tightening of controls) episodes using the Updated CCM Dataset. For each event, we track the evolution of scaled fund flows within a $[-12, +12]$ month event window, where $t = 0$ denotes the month of policy implementation. As shown by the green trajectory in Figure **??**, liberalizing measures are associated

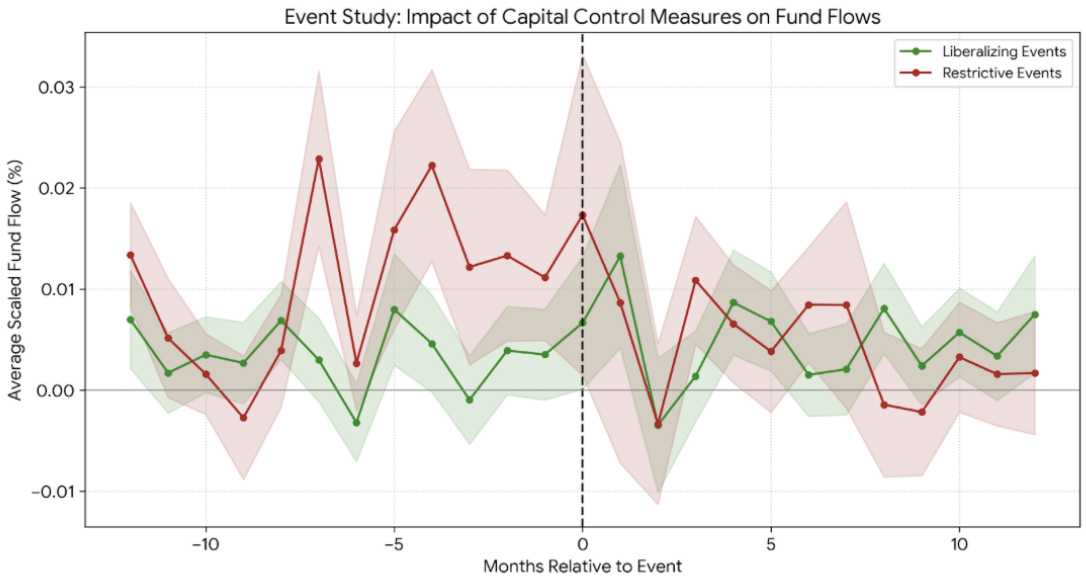


Figure 16. Event Study

with an immediate positive response in fund inflows. Fund flows begin to rise sharply at $t = 0$ and peak at $t = 1$, suggesting that global investors respond quickly to signals of market opening. However, this increase is short-lived: inflows revert toward their pre-event levels by $t = 2$, consistent with a temporary "relief rally" or short-run portfolio rebalancing rather than a persistent change in capital allocation trends.

The red trajectory in Figure 18 reveals a distinct counter-cyclical pattern. Restrictive measures tend to be implemented during periods of unusually strong inflows, with fund flows peaking around $t = 0$. This timing is consistent with the interpretation that policymakers deploy capital controls in response to surging capital inflows or overheating pressures. Following the introduction of restrictions, fund flows decline sharply in the subsequent months ($t = 1$ and $t = 2$), shifting from net inflows toward neutral or net outflows. The magnitude and speed of this reversal indicate that restrictive measures are effective at dampening short-run capital inflow pressures.

To examine whether the effects of fund flow vary with a country's level of financial development, we extend the baseline event study by stratifying countries according to their average Financial Development (FD) Index. We classify policy events into *Liberalizing* and *Restrictive* episodes, and divide countries into three

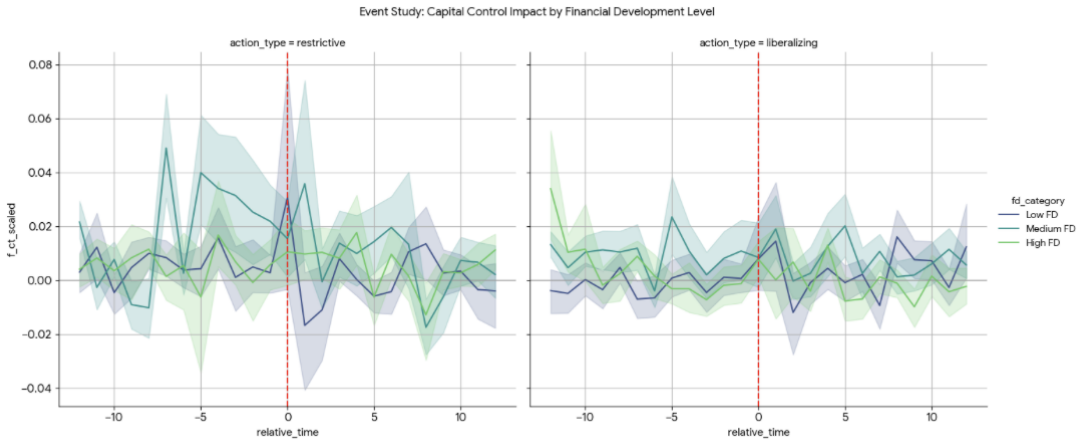


Figure 17. Caption

groups—*Low*, *Medium*, and *High* FD—based on terciles of the FD distribution. For each group, we track scaled fund flows within a $[-12, +12]$ month window around the event month ($t = 0$).

Figure 17 presents the results. The left panel reports responses to liberalizing actions. In high-FD countries, fund flows exhibit only muted movements around the event date, indicating that in financially developed markets capital allocation is largely driven by fundamentals and deep market structures, such that marginal easing of capital controls generates limited additional inflows. In contrast, low- and medium-FD countries display a more pronounced positive response following liberalization. In particular, low-FD countries experience a noticeable increase in inflows after $t = 0$, consistent with a "breakthrough" effect whereby capital account opening alleviates binding frictions and attracts foreign capital.

The right panel shows responses to restrictive actions. High-FD countries again exhcibit minimal reactions, with fund flows remaining close to zero throughout the event window. This pattern suggests that in financially developed economies, capital control measures are often targeted or macroprudential in nature and do not trigger broad-based capital flight. By contrast, low-FD countries experience a sharp deterioration in fund flows around restrictive events, with inflows turning negative in the months surrounding implementation. This pattern may reflect both policy endogeneity, where restrictions are introduced in response to incipient capital outflows, and amplification effects, whereby tightening measures exacerbate investor concerns and induce preemptive or accelerated capital withdrawal.

Overall, the results indicate that the effectiveness and consequences of capital control policies are strongly mediated by a country's level of financial development. Capital control actions have substantially larger effects on cross-border fund flows in countries with lower financial development, while appearing largely inconsequential in high-FD economies.

Specific Country Event Study The aggregate analysis reveals substantial cross-country heterogeneity in the effects of inward capital controls. To illustrate and further explore this heterogeneity, we then focus on three economically and financially important countries—China, Australia, and the United States—and conduct country-specific event studies. The results highlight pronounced differences in both the magnitude and dynamics of fund flow responses across these countries, underscoring the importance of country-specific institutional and financial characteristics in shaping the transmission of capital control policies.

For each capital control event, we define an event window of 13 months, spanning from six months before to six months after the policy implementation date. The dependent variable is the percentage change in fund flow relative to assets at the beginning of the month, denoted as `flowpct`. We assign an event time variable $t \in [-6, +6]$ for each observation in the window, where $t = 0$ indicates the month of the policy event.

The main regression specification is as follows:

$$\texttt{FlowAllocation}_{it} = \sum_{\tau=-6}^{+6} \sum_{k \in \{\text{L,R}\}} \beta_{\tau}^{k} \cdot \mathbb{1}\{t = \tau \text{ and } \texttt{Intensity} = k\} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{11}$$

where $\mathbb{1}\{\cdot\}$ is an indicator function for event time τ and action intensity k. α_i denotes fund fixed effects, and γ_t captures global month fixed effects. The coefficients β_{τ}^{k} trace the average treatment effect of each policy type over time. Standard errors are clustered at the fund or country level. For descriptive analysis, we additionally plot the average `flowpct` over the event window by policy type, with 95% confidence intervals constructed using standard errors of the mean. The event study plot shows in follows.

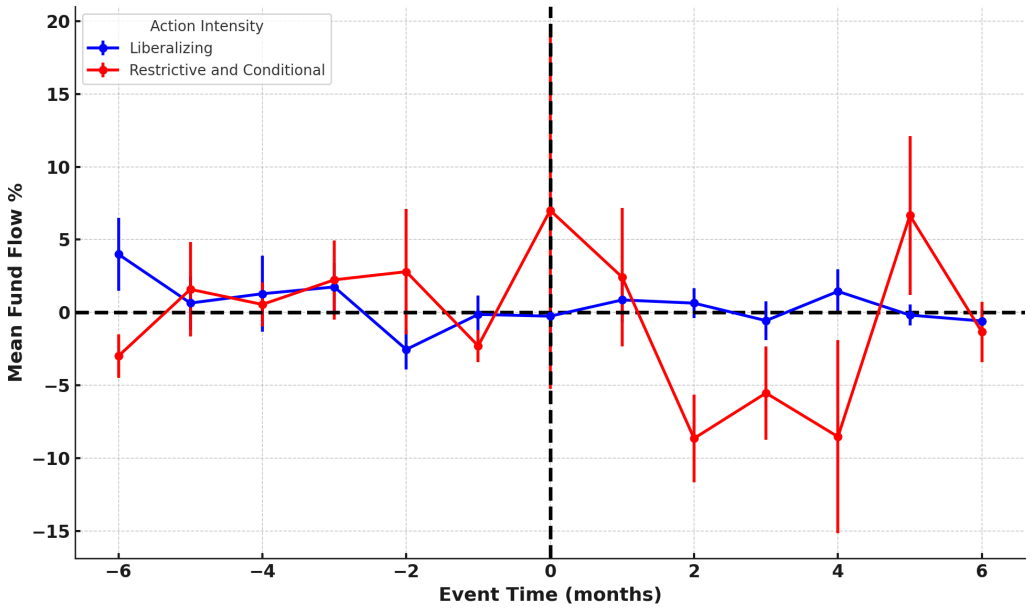


Figure 18. Event Study Analysis: A Case Study of China

For the case study of China in Figure 18, the red line represents the average fund flow percentage around the implementation of restrictive or conditional capital inflow measures, while the blue line corresponds to liberalizing interventions. The event study reveals notable patterns. Restrictive and conditional inward capital control policies introduced by China are associated with a significant decline in fund inflows: Before implementing capital control policies, the average fund flow into China was quite stable. Starting approximately one month after implementation, the average fund flow percentage drops, reaching a cumulative decline of around 8% within three months. In contrast, liberalizing policies exhibit only a modest effect on capital inflows after implementing the loosening policies, and last for 2 months.

The case of Australia and the US exhibits a distinct pattern, as shown in Figure 19 and Figure 20. Fund flows were significantly positive in the months preceding the implementation of restrictive and conditional capital control measures. However, the effects taper off and become statistically insignificant immediately after the policy interventions, remaining close to zero for several months. Notably, a significant reflow of capital into Australia is observed approximately four months after the intervention. This suggests that the impact of restrictive capital controls in Australia persists for up to four months. In contrast, liberalizing capital account interventions appear to have no significant effect on boosting fund inflows

upon implementation.

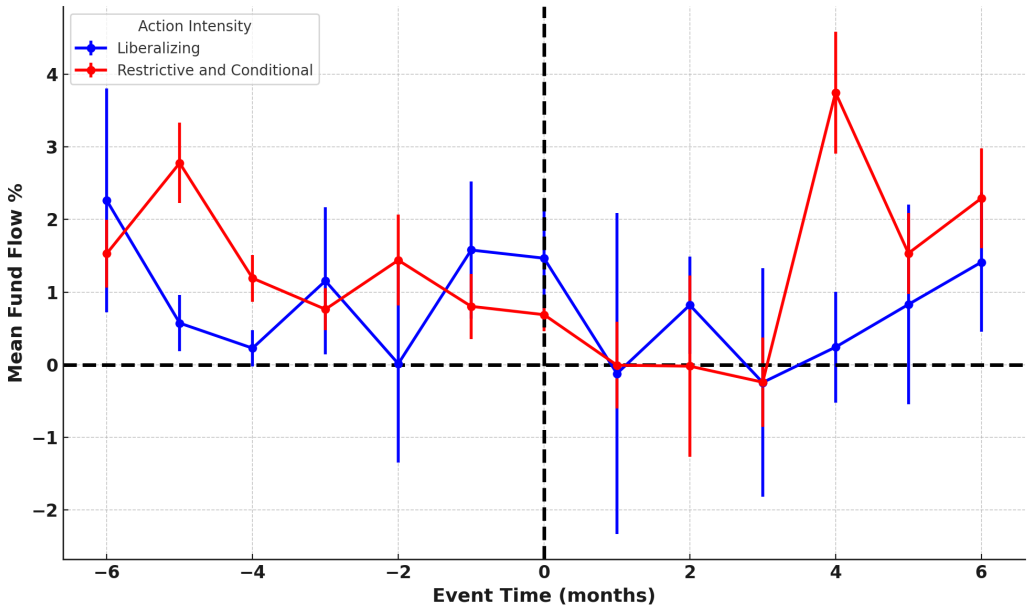


Figure 19. Event Study Analysis: A Case Study of Australia

A particularly interesting pattern regarding action intensity emerges in the case of the United States. The effects of liberalizing and restrictive measures exhibit opposite dynamics around the time of implementation. Inward-oriented restrictive capital control measures show a statistically significant impact only in the month of implementation, after which capital inflows remain positive and continue on an upward trend. Surprisingly, liberalizing measures also produce a short-term significant increase in fund inflows; however, this effect is temporary, as inflows revert to their pre-intervention levels shortly thereafter.[12] These event-level findings underscore the potential for future research to further investigate the nuanced and heterogeneous effects of capital control intervention.

[12]This figure presents a preliminary example of the event study results. To assess robustness, additional methods and specifications can be employed to validate the effects of capital control measures. Due to space constraints, we leave a detailed robustness analysis to a separate paper.

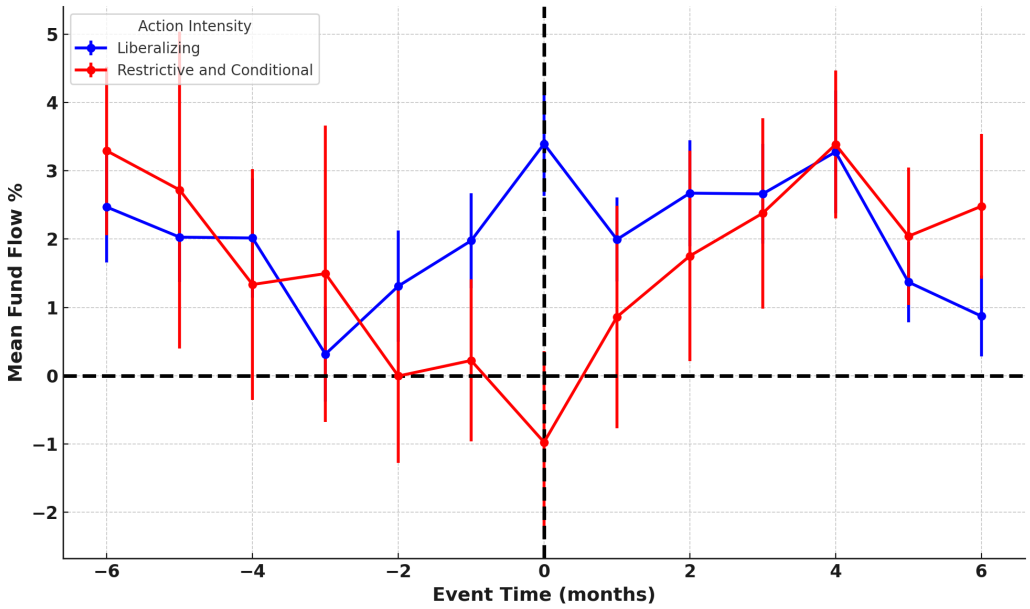


Figure 20. Event Study Analysis: A Case Study of the US

4.2.1 Panel Regressions

Country-Level Regression. We begin with a baseline country-level regression that examines the average relationship between restrictive capital control measures and fund flows using a two-way fixed effects framework. This specification exploits within-country variation over time while controlling for unobserved country-specific characteristics and common global shocks through country and time fixed effects.

The coefficient β_1 captures the average effect of restrictive capital control measures on fund flows across countries, abstracting from potential cross-country heterogeneity. This baseline specification serves as a benchmark against which subsequent analyses—introducing policy changes, forceful policy episodes, and heterogeneous effects—are compared.

$$Flow_{c,t} = \beta_1 CC_{c,t} + \mathbf{X}'_{c,t}\gamma + \alpha_c + \mu_t + \varepsilon_{c,t}, \tag{12}$$

Table 6 reports summary statistics for the main variables used in the analysis. The dependent variable, scaled fund flows, exhibits substantial variation across countries and over time, with a mean close to zero and sizable dispersion, reflecting pronounced heterogeneity in cross-border fund movements. Countries in the

sample display meaningful variation in financial development, with the Financial Development Index ranging from 0.15 to 1.00. Global financial conditions, as proxied by the VIX and the global financial conditions index, also vary substantially over the sample period, capturing periods of heightened global risk and financial stress. Standard macroeconomic controls, including GDP growth, inflation, interest rates, and exchange rate indicators, exhibit wide dispersion, highlighting the importance of controlling for both domestic fundamentals and global push factors in the empirical analysis.

Table 6. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
$f_{c,t}^{scaled}$ (Fund Flows)	9,980	0.0018	0.0594	-0.6098	1.1852
Restrictive Frequency	9,980	0.0463	0.3613	0	13
Liberalizing Frequency	9,980	0.0550	0.3698	0	9
Restrictive Dummy	9,980	0.0290	0.1677	0	1
Liberalizing Dummy	9,980	0.0345	0.1824	0	1
Number of Funds	9,980	172.72	157.90	1	961
Financial Development (FD Index)	6,736	0.5814	0.2044	0.147	1.000
VIX	3,293	18.99	8.33	10.26	62.67
GDP Growth (%)	3,081	2.31	3.34	-9.88	24.62
Effective Federal Funds Rate	3,293	0.31	0.52	0.04	3.22
Monthly CPI Index	2,850	99.24	11.58	56.39	238.62
Shadow Policy Rate	3,293	-0.73	1.27	-2.99	2.66
Global Financial Conditions Index	3,177	66.22	10.48	42.06	89.35
Exchange Rate Index	3,117	0.5435	0.3364	0.112	1.000
Monetary Independence Index	3,115	0.3620	0.2826	0	1

Figure 21 reports pairwise correlations among fund flows, restrictive capital control measures, and macro-financial controls. The restrictive dummy is positively and statistically significantly correlated with fund flows, indicating systematic comovement between the implementation of restrictive measures and capital flow dynamics, while the magnitude of the correlation remains modest. In the meanwhile, we also plot the time-series trajectory of standardized fund flows for the top nine countries in Figure 22. To distinguish between idiosyncratic monthly volatility and persistent structural shifts, we plot both the raw data (light gray lines) and a smoothed 6-month moving average (solid blue lines).

Developed economies, such as Australia and Canada, exhibit a "Mean-Reverting" pattern. While their raw monthly data (gray lines) shows frequent fluctuations, the

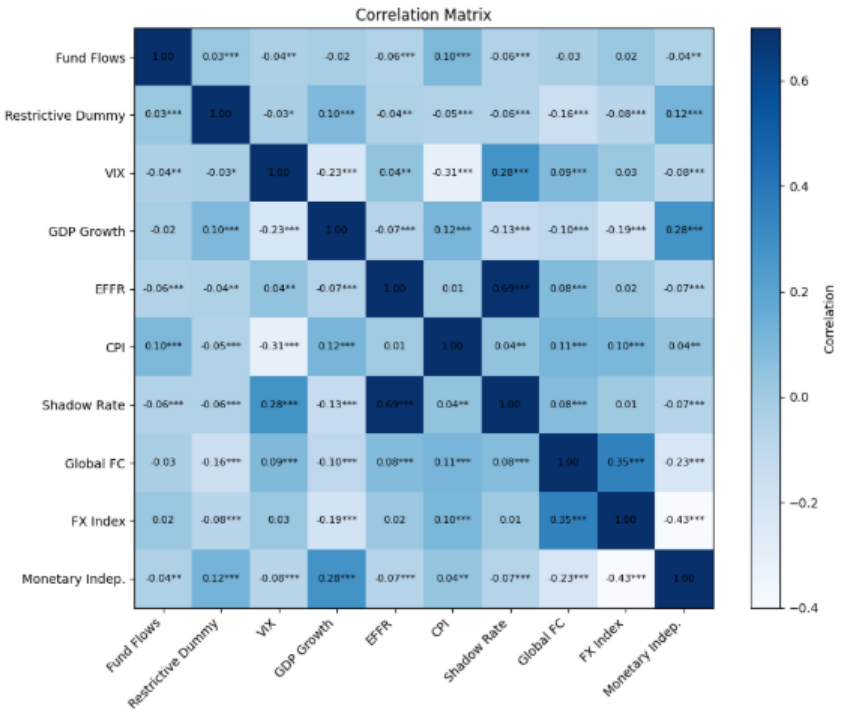


Figure 21. Pairwise correlations

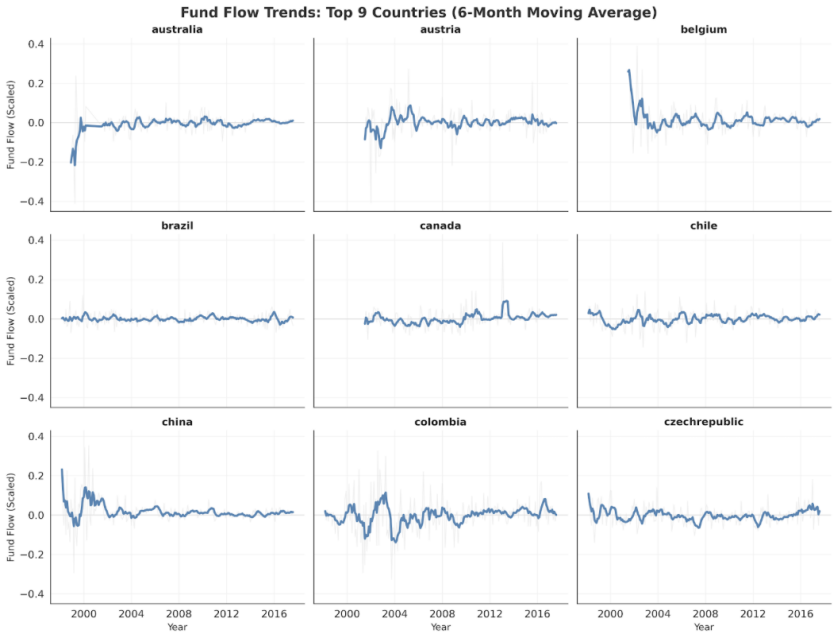


Figure 22. Standardized fund flows (Top 9 AUM)

smoothed trend (blue lines) remains relatively stable around the zero threshold, suggesting mature and balanced capital markets. In contrast, emerging markets like Brazil display a "High-Volatility/Cyclical" morphology. Brazil shows substantial surges in inflows followed by deep, sustained retrenchments, particularly following the 2008 Global Financial Crisis and during the commodity price fluctuations of 2013, reflecting high sensitivity to the global financial cycle.

Furthermore, countries such as Austria and Belgium demonstrate "Regional Synchronization," with their flows closely tracking Eurozone-wide shocks. Other nations exhibit "Event-Driven" spikes, where vertical impulses in the raw data correspond to specific domestic macro-shocks or policy announcements. These distinct cross-country dynamics underscore the necessity of employing country-fixed effects in our subsequent econometric analysis to control for unobserved time-invariant institutional characteristics.

Table 7 examines how capital control measures affect monthly country-level fund flows, distinguishing between aggregate policy intensity, policy composition, and forceful policy episodes. The dependent variable is monthly fund flows scaled by lagged assets under management, and all specifications include country and month fixed effects, with standard errors clustered at the country level.

The aggregate capital control index (*Total index*) measures the total frequency of capital control actions implemented in a given country-month, aggregating all capital control measures regardless of direction. This index captures the overall intensity of capital control activity at the monthly frequency. Across specifications, the coefficient on the total index is negative and statistically significant once macroeconomic controls are included, indicating that months with more active capital control interventions are associated with lower fund inflows. To assess whether this effect is driven by specific types of policy actions, Columns (3)–(6) decompose the aggregate index into policy components. The restrictive and liberalizing frequencies are precisely classified as tightening or loosening actions based on their legal and operational content. These frequency measures capture the number of tightening and liberalizing interventions within each country-month. The corresponding dummy variables indicate the presence of at least one such measure.

Columns (3) and (4) further distinguish between forceful tightening and forceful loosening episodes, following the identification strategy of Chang (2024). Specifically, as equation 13, 14 and 15 shows, forceful policy changes are defined as discrete jumps in the capital control index that exceed 2.5 standard deviations from

the mean of positive or negative changes, respectively. These episodes capture unusually large and salient shifts in the capital control regime, rather than incremental adjustments. Columns (5) and (6) further examine the role of policy changes and policy composition in driving fund flow responses. Column (5) replaces the level of the aggregate capital control index with its monthly change, thereby isolating the impact of newly introduced or withdrawn capital control measures. The coefficient on the change in the total index is negative and statistically significant, indicating that policy adjustments—rather than the prevailing level of controls—trigger immediate fund outflows. This result highlights the importance of policy changes and announcement effects in shaping investor behavior.

Column (6) provides an additional robustness check by excluding the aggregate index altogether and focusing solely on policy components and forceful episodes. The results show that forceful tightening remains strongly negative and statistically significant, while forceful loosening exhibits a weaker offsetting effect. The persistence of these results in the absence of the aggregate index suggests that the effects of forceful policy actions are not mechanically driven by the overall frequency of capital control measures, but instead reflect economically meaningful responses to salient and large regulatory interventions.

Taken together, Columns (5) and (6) reinforce the interpretation that fund flows respond primarily to discrete and forceful changes in the capital control regime, rather than to gradual adjustments or the accumulation of routine policy actions.

$$\Delta \text{CC}_{i,t} = \text{CC}_{i,t} - \text{CC}_{i,t-1} \tag{13}$$

$$\text{Forceful tightening if } \Delta \text{CC}_{i,t} \geq \mu_{\Delta>0} + 2.5\sigma_{\Delta>0} \tag{14}$$

$$\text{Forceful loosening if } \Delta \text{CC}_{i,t} \leq \mu_{\Delta<0} - 2.5\sigma_{\Delta<0} \tag{15}$$

The results indicate that the negative effect of capital controls on fund flows is driven primarily by forceful tightening episodes. Forceful tightening is associated with a large and statistically significant decline in fund inflows, while forceful loosening has a smaller and weaker offsetting effect. Importantly, these results remain robust when the aggregate index is excluded, indicating that the forceful components capture economically meaningful variation beyond the overall level of policy activity. Taken together, the evidence suggests that investors respond disproportionately to salient and forceful tightening of capital controls, rather than to grad-

ual changes or the accumulation of routine policy actions. This finding highlights the importance of policy intensity and salience in shaping cross-border portfolio allocation decisions.

From Table 7, we also observe a robust and economically meaningful relationship between financial development and fund flows. Across specifications, the coefficient on financial development is negative and statistically significant, indicating that countries with higher levels of financial development tend to experience larger fund outflows, conditional on capital control policies and macroeconomic fundamentals.

This finding is consistent with the view that financially more developed countries provide deeper and more flexible financial markets, which facilitate cross-border portfolio reallocation and capital mobility. As a result, investors in these countries may respond more actively to changes in the global financial environment and domestic policy conditions, leading to greater outward fund flows. Importantly, this result suggests that the impact of capital control measures may not be homogeneous across countries. Instead, the effectiveness of capital controls is likely to depend on a country's level of financial development, which shapes both investors' ability to adjust portfolios and the enforcement capacity of regulatory measures.

Heterogeneous Regression Analysis Motivated by the preceding results, this section examines whether the effects of capital control measures vary systematically with the level of financial development, shows in equation 16. In particular, we introduce interaction terms between capital control indicators and financial development to test for heterogeneous policy effects across countries with different degrees of financial sophistication. This specification allows the responsiveness of fund flows to capital control measures to differ depending on a country's financial development, reflecting variation in market depth, investor mobility, and regulatory capacity.

Specifically, we estimate the following interaction specification:

$$f_{c,t} = \beta_1 \mathrm{CC}_{c,t} + \beta_2 \mathrm{FD}_{c,t} + \beta_3 \left(\mathrm{CC}_{c,t} \times \mathrm{FD}_{c,t}\right) + \mathbf{X}'_{c,t}\gamma + \alpha_c + \delta_t + \varepsilon_{c,t}, \tag{16}$$

Table 8 examines whether the effects of capital control measures vary systematically with the level of financial development by introducing interaction terms between capital control indicators and financial development. Column (1) focuses

Table 7. Capital Control Stance, Policy Components, and Monthly Fund Flows

	(1) Baseline f_{ct}^{scaled}	(2) + Controls f_{ct}^{scaled}	(3) + Policy Components f_{ct}^{scaled}	(4) Decomposition f_{ct}^{scaled}	(5) Changes f_{ct}^{scaled}	(6) Components Only f_{ct}^{scaled}
Total index	-7.88×10^{-7}	-2.05×10^{-6}**	-2.06×10^{-6}**	-2.03×10^{-6}**		
	(7.81×10^{-7})	(9.09×10^{-7})	(9.08×10^{-7})	(9.07×10^{-7})		
Forceful tightening				−0.0272***		−0.0277***
				(0.0071)		(0.0070)
Forceful loosening				0.0058*		0.0058*
				(0.0033)		(0.0033)
Δ Total index					−0.00249**	
					(0.00092)	
Restrictive frequency			0.0019	0.0021		0.0020
			(0.0015)	(0.0015)		(0.0015)
Liberalizing frequency			−0.0024	−0.0025		−0.0025
			(0.0027)	(0.0027)		(0.0027)
Restrictive dummy			−0.0018	−0.0018		−0.0019
			(0.0056)	(0.0055)		(0.0055)
Liberalizing dummy			0.0031	0.0036		0.0036
			(0.0062)	(0.0060)		(0.0060)
FD value		−0.0644**	−0.0640**	−0.0648**	−0.0575*	−0.0587*
		(0.0294)	(0.0296)	(0.0295)	(0.0282)	(0.0283)
Macro controls	No	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Clusters (country)	32	21	21	21	21	21
Observations	2,841	1,860	1,860	1,860	1,860	1,860
R^2	0.174	0.199	0.199	0.200	0.200	0.200

Notes: The dependent variable is monthly country-level fund flows scaled by lagged assets under management. Column (5) replaces the level of the capital control index with its monthly change, $\Delta CC_{c,t}$, capturing newly introduced or withdrawn capital control measures. All regressions include country and month fixed effects. Standard errors clustered at the country level are reported in parentheses. Macro controls include financial development, inflation, growth, and policy indices. Global variables collinear with month fixed effects (e.g., VIX, policy rates) are omitted. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 8. Financial Development and Heterogeneous Effects of Capital Controls

	(1) Changes × FD f_{ct}^{scaled}	(2) Levels × FD f_{ct}^{scaled}
Δ Total index	−0.0046	
	(0.0032)	
Total index		0.00003
		(0.00002)
Financial development (FD)	−0.0578*	−0.0672**
	(0.0284)	(0.0300)
Δ Total index × FD	0.0028	
	(0.0041)	
Total index × FD		−0.00003
		(0.00002)
Macro controls	Yes	Yes
Country FE	Yes	Yes
Month FE	Yes	Yes
Clusters (country)	21	21
Observations	1,860	1,860
R^2	0.200	0.199

Notes: The dependent variable is monthly country-level fund flows scaled by lagged assets under management. Column (1) interacts financial development with changes in the aggregate capital control index, while Column (2) interacts financial development with the level of the index. All regressions include country and month fixed effects. Standard errors clustered at the country level are reported in parentheses. Macro controls include growth, inflation, financial openness, and institutional indices. ** and * denote significance at the 5% and 10% levels, respectively.

on policy changes by interacting financial development with changes in the aggregate capital control index, while Column (2) considers policy levels by interacting financial development with the level of the index. These results imply that financial development shapes the overall propensity for cross-border capital reallocation, but it does not act as a systematic amplifier of the effects of capital control measures. In other words, while financially developed countries exhibit greater baseline capital mobility, the short-run response of fund flows to capital control policies appears broadly similar across countries, consistent with the notion that capital control actions, trigger investor responses that are largely independent of domestic financial sophistication.

While the interaction terms between financial development and capital control measures are statistically insignificant in the aggregate, this finding does not rule out the possibility of heterogeneous effects at a more granular policy level. The analysis in this paper focuses on aggregate indices and broad policy categories, which capture the overall stance and intensity of capital control regimes. However, different types of capital control measures—such as restrictions on portfolio inflows versus outflows, quantity-based versus price-based instruments, or measures targeting specific asset classes—may interact with financial development in distinct ways.

Future research could exploit more detailed classifications of capital control policies to examine whether financial development differentially shapes the effectiveness of specific instruments. For example, financially more developed countries may respond more strongly to controls targeting sophisticated financial instruments or cross-border portfolio flows, while less developed financial systems may be more sensitive to restrictions on banking flows or foreign exchange transactions. Exploring such policy-level heterogeneity would provide further insight into the channels through which capital controls operate and help reconcile aggregate null results with potentially rich cross-instrument variation.

5 Conclusion

This paper overcomes several limitations in the empirical literature on capital controls. We develop a new event-level Capital Control Measures (CCM) dataset, based on the IMF's AREAER reports and leveraging prompt-based large language models (GPT-4.1 OpenAI (2025)) and modern natural language processing (NLP) techniques. Using textual analysis, we enrich the measurement of capital control interventions with multidimensional characteristics, including action type, action intensity, action direction, implementing actor, target country, target industry, and several binary indicators such as whether the measure is related to trade policy, national security, or sanctions. The stylized facts derived from the CCM dataset reveal distinct patterns around major global episodes, such as the 2008 financial crisis and the COVID-19 pandemic, and highlight heterogeneity across different income and regional country groups. Applying the CCM dataset in a comprehensive empirical framework, this paper examines how capital control interventions shape global fund flows using a large-scale, monthly country-level panel. Moving beyond country-specific event studies, we document robust average effects of capital control measures on fund flows while explicitly accounting for policy intensity, policy composition, and discrete policy adjustments.

Our results show that restrictive capital control measures are systematically associated with fund outflows, particularly when policies involve forceful tightening or salient regime changes, whereas liberalizing measures exhibit more limited and less robust effects. Importantly, the analysis reveals substantial variation in the responses of fund flows across policy types and policy magnitudes, highlighting the importance of distinguishing between routine policy actions and large, nonlinear interventions. While financial development is a key determinant of baseline capital mobility, we find limited evidence that it systematically amplifies the short-run effects of capital control measures, suggesting that investor responses to policy interventions are broadly similar across countries in the short run.

To automate the categorization process and develop a model that generalizes to other sources of capital control events, we finetune an open-sourced large language model based on Meta Llama 3.1 (Grattafiori et al., 2024). We refer to the resulting model as *CCM-Llama*. To support this effort, we construct a rigorous data collection pipeline and compile a large-scale finetuning dataset comprising 29,012 examples. Our finetuned model achieves 99.55% accuracy on the binary classification task

and up to 90.09% accuracy on the hierarchical classification task, outperforming all baselines including the state-of-the-art commercial model. A key advantage of *CCM-Llama* lies in its ability to incorporate multiple sources of policy measures and to provide real-time classification of capital control events from external sources such as market news and central bank announcements. This capability enables future researchers and investors to continuously monitor and analyze the evolving dynamics of global financial markets.

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A Description of Capital Control Categories

Appendix Table A1. Capital Control Category Descriptions (Multi-Page)

Index	Category	Description
XI.A.	Controls on capital transactions [ka]	Restrictions on cross-border capital flows, covering investment, credit, and real estate transactions.
XI.A.2.	Controls on capital and money market instruments	Rules regulating international transactions in equity, debt, money markets, and investment funds.
XI.A.2.a.	On capital market securities	Measures on shares and bonds issued or acquired by residents or nonresidents.
XI.A.2.a.1.	Shares or other securities of a participating nature [eq]	Controls on equity investments involving ownership or participation rights.
XI.A.2.a.1.i	Purchase locally by nonresidents [eq_plbn]	Restrictions on foreigners buying domestic equity locally.
XI.A.2.a.1.iv	Sale or issue abroad by residents [eq_siar]	Controls on residents issuing or selling equity abroad.
XI.A.2.a.1.iii	Purchase abroad by residents [eq_pabr]	Measures on residents buying equity in foreign markets.
XI.A.2.a.1.ii	Sale or issue locally by nonresidents [eq_siln]	Regulations on foreigners issuing equity locally.
XI.A.2.a.2.	Bonds or other debt securities [bo]	Controls on transactions in debt instruments like bonds and notes.
XI.A.2.a.2.i	Purchase locally by nonresidents [bo_plbn]	Restrictions on foreigners purchasing domestic bonds.

Continued on next page

Index	Category	Description
XI.A.2.a.2.iv	Sale or issue abroad by residents [bo_siar]	Controls on residents issuing debt securities abroad.
XI.A.2.a.2.iii	Purchase abroad by residents [bo_pabr]	Measures on residents buying foreign bonds.
XI.A.2.a.2.ii	Sale or issue locally by nonresidents [bo_siln]	Regulations on foreign entities issuing debt locally.
XI.A.2.b.	On money market instruments [mm]	Rules concerning short-term securities such as T-bills and commercial paper.
XI.A.2.b.1	Purchase locally by nonresidents [mm_plbn]	Controls on foreigners buying domestic money market instruments.
XI.A.2.b.4	Sale or issue abroad by residents [mm_siar]	Restrictions on residents issuing money market instruments abroad.
XI.A.2.b.3	Purchase abroad by residents [mm_pabr]	Regulations on residents acquiring money market instruments abroad.
XI.A.2.b.2	Sale or issue locally by nonresidents [mm_siln]	Measures on nonresidents issuing short-term instruments domestically.
XI.A.2.c.	On collective investment securities [ci]	Controls on cross-border transactions in mutual funds and similar vehicles.
XI.A.2.c.3	By residents to nonresidents [cio]	Restrictions on domestic collective vehicles selling to nonresidents.
XI.A.2.c.1	By nonresidents to residents [cii]	Controls on foreign investment vehicles marketed to residents.
XI.A.3.	Controls on derivatives and other instruments	Measures regulating cross-border transactions in financial derivatives.

Continued on next page

Index	Category	Description
XI.A.3.a.	Purchase locally by nonresidents	Restrictions on nonresidents buying derivatives locally.
XI.A.3.b.	Sale or issue locally by nonresidents	Regulations on foreigners issuing derivatives domestically.
XI.A.3.c.	Purchase abroad by residents	Controls on residents acquiring foreign derivatives.
XI.A.3.d.	Sale or issue abroad by residents	Restrictions on residents issuing derivatives overseas.
XI.A.4.	Controls on credit operations	Rules on lending, guarantees, and financial credit between residents and nonresidents.
XI.A.4.b.	Financial credits [fc]	Regulations on cross-border financial loans and credit lines.
XI.A.4.b.1	By residents to nonresidents [fco]	Controls on residents providing financial loans abroad.
XI.A.4.b.2	By nonresidents to residents [fci]	Measures on foreign entities lending to domestic parties.
XI.A.4.a.	Commercial credits	Measures on trade-related deferred payment and credit agreements.
XI.A.4.a.1	By residents to nonresidents	Restrictions on trade credits extended by residents abroad.
XI.A.4.a.2	To residents from nonresidents	Controls on commercial credit provided by foreign parties.
XI.A.4.c.	Guarantees, sureties, and financial backup facilities	Controls on financial guarantees supporting cross-border financial operations.
XI.A.4.c.1	By residents to nonresidents	Restrictions on guarantees extended by residents to foreigners.

Continued on next page

Index	Category	Description
XI.A.4.c.2	To residents from nonresidents	Measures on financial backing offered to residents by nonresidents.
XI.A.7.	Controls on real estate transactions	Measures restricting cross-border property ownership or sales.
XI.A.7.a.	Purchase abroad by residents	Restrictions on residents buying property overseas.
XI.A.7.b.	Purchase locally by nonresidents	Controls on foreigners acquiring domestic real estate.
XI.A.7.c.	Sale locally by nonresidents	Regulations on foreign owners selling property domestically.
XI.A.5.	Controls on direct investment [di]	Rules managing long-term cross-border investments involving control or influence.
XI.A.5.a	Outward investment [dio]	Controls on domestic entities investing directly abroad.
XI.A.5.b	Inward direct investment [dii]	Measures on foreign direct investment into domestic firms.
XI.A.5.c	Liquidation of direct investment [ldi]	Regulations on the repatriation of capital from divested investments.

B AREAER Country Mapping

Appendix Table A2. Country Name Mappings

Original Name	**Standardized Name**
Türkiye	Turkey
Hong Kong SAR	Hong Kong
Hong Kong Special Administrative Region	Hong Kong
Democratic Republic of the Congo (DRC)	Democratic Republic of the Congo
Democratic Republic of the Congo	Democratic Republic of the Congo
Republic of Korea	South Korea
Korea	South Korea
Islamic Republic of Iran	Iran
Republic of Yemen	Yemen
Syrian Arab Republic	Syria
Lao P.D.R.	Laos
Lao People's Democratic Republic	Laos
People's Republic of China	China
People's Republic of China—Hong Kong SAR	Hong Kong
Swaziland	Eswatini
Kingdom of Eswatini	Eswatini
Cape Verde	Cabo Verde
República Bolivariana de Venezuela	Venezuela
República Bolivariana De Venezuela	Venezuela
Russian Federation	Russia
Papua New-Guinea	Papua New Guinea
Federated States of Micronesia	Micronesia
Serbia and Montenegro	Serbia
Republic of Serbia	Serbia
Republic of Montenegro	Montenegro
Islamic Republic of Afghanistan	Afghanistan
Islamic State of Afghanistan	Afghanistan
Czech Republic	Czechia
Former Yugoslav Republic of Macedonia	North Macedonia
Republic of North Macedonia	North Macedonia
Republic of Congo (Congo)	Republic of Congo
Democratic Republic of Timor-Leste	Timor-Leste
Republic of Azerbaijan	Azerbaijan
Republic of Fiji	Fiji
Socialist People's Libyan Arab Jamahiriya	Libya