AFPs Withdrawals: An Event Study Analysis

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Abstract

This study examines how five major AFP withdrawal discussion dates affected Peruvian equities between 2020 and 2024. Using an event-study framework, we analyze the SP&BVL index and 14 actively traded BVL stocks with persistent AFP ownership. Expected returns are estimated in a 120-trading-day pre-event window (120 to 31) with a multifactor model that includes S&P 500 returns, copper returns, and changes in Peru's 5-year CDS. Abnormal returns are cumulated into CARs for windows from 15 to +30 trading days, and significance is evaluated with standardized tests and joint $J1/J2$ statistics across events and portfolio constructions. Results show that reactions became more negative in the later episodes: the 2022 and 2024 events display sharp declines, with index CARs around 12% and 10% over the +1 to +15 window. For the 14-stock sample, the equally weighted portfolio has statistically significant negative CARs after the events, whereas the value-weighted portfolio is close to zero and mostly insignificant, consistent with heavy concentration in a few large-cap firms. Overall, the evidence suggests that policy-driven liquidity shocks can create short-run price pressure in Peru's thin and concentrated equity market.

1 Introduction

During the last 5 years, from 2020 to 2025, 8 withdrawals were approved by the Peruvian Congress. These withdrawals have received extensive media coverage and raised concerns among regulators, the government, financial institutions, and the general public. The pension funds are players in the Peruvian capital markets, so analyzing withdrawals is relevant for understanding how the Peruvian stock market value could have been affected.

Additionally, there are some studies and publications related to the withdrawals. However, there has been little quantitative analysis of the relationship between pension fund withdrawals and their impact on Peruvian capital markets. Given the available data on prices and pension fund portfolio compositions, we can assess the potential impact of these withdrawals.

The Peruvian private pension fund system (Administradoras de Fondos de Pensiones, AFPs) was established in 1993 as part of a structural reform intended to complement and partially replace the public pension system. Currently, there are four AFPs operating in Peru—Integra, Prima, Profuturo, and Hábitat—managing funds across five portfolio types that differ in risk exposure and investment limits. These institutions play a central role in the domestic capital market, holding significant shares of sovereign bonds and equities listed on the Lima Stock Exchange (Bolsa de Valores de Lima, BVL).

AFPs have a significant importance in the Peruvian economy and capital markets. Their asset under management (AUM) represent PEN 107 billion (USD 28.3 billion), which represents approximately 10% of Peru's GDP. Their investment in the local stock market represents 2.72% of Lima Stock Market Capitalization as of December 2024. The AFPs represent 9.72% of Peruvian Sovereign Bonds, down from 16.26% in December 2023, and are the third-largest investor, behind only foreign holders and banks. Therefore, private pension funds are relevant to the economy, the Peruvian stock market, and the fixed-income market.

AFPs invest in different types of instruments, sectors, and geographies. Additionally, AFPs allocate their portfolio across four funds, ranging from type 0 (most conservative) to type 3 (most aggressive). They invest the most in type 1, with 19bn (or 17.8%), and type 2, with 69bn (or 64.4%). AFPs' portfolio main investment limits are regulated by Law 29759-2011 (50% on foreign investments) and the SBS Regulation 63926-2024, which defines limits and sublimits by asset class and fund type.

Peruvian pension funds have historically limited their foreign investments—a policy choice that precludes adequate international diversification and reinforces systemic exposure to domestic market volatility. Peruvian pension funds derive a significant share of their profits from their domestic portfolios, which are mandated by regulation. Within these holdings, the primary source of returns comes from equity investments. However, this income structure exposes Peruvian savers to substantial earnings volatility, given the local stock market's limited liquidity, high concentration, and elevated risk.

Pension funds' objective is to maximize returns, subject to the risk appetite of the pension contributors. At the end of the person's cycle, they should receive the best possible pension retirement; therefore, the pension fund must give the highest potential returns for its members.

The issue of the last five years (since 2020) is the unprecedented series of pension withdrawals approved in Peru between 2020 and 2024, which provides a unique quasi-experimental setting to examine the impact of large, exogenous regulatory shocks on financial markets. Each withdrawal compelled private pension fund administrators (Administradoras de Fondos de Pensiones, AFPs) to liquidate assets to meet liquidity demands, thereby altering portfolio allocations and potentially influencing asset prices, volatility, and trading volumes. Analyzing these events offers valuable insight into investor behavior under regulatory stress and the transmission of liquidity shocks to the capital market.

This study examines the effects of seven AFP withdrawal announcements on the equity performance of firms with significant pension-fund ownership using the event-study methodology. Specifically, we evaluate cumulative abnormal returns (CARs) for 14 actively traded BVL stocks within defined event windows around each withdrawal announcement, using 120 trading days of pre-event data to estimate expected returns. Statistical significance is assessed through both individual and joint hypothesis tests, enabling a comprehensive evaluation of the short-term market reactions induced by these regulatory interventions.

2 Literature Review

This document is framed within the literature on the effects of regulation on financial markets. In this case, the regulation affects institutional investors' expectations, rebalancimarket participants' reactionsants, and how local financial markets behave.

The current literature shows that investment policy portfolio rebalancing can affect the aggregate prices of bonds and stocks (Harvey et al., 2025). The actions of institutional investors can impact the equity, bond, and foreign exchange markets. Portfolio rebalancing among institutional investors involves selling the most performant stocks based on concentration risk criteria, which may affect stock prices (Chen 2024). Demand shifts by institutional investors may affect government bond yields (Jansen 2021). Rebalancing, driven by international equity outperformance, leads to foreign exchange appreciation as capital is repatriated to restore portfolio balance between equity and stocks (Camanho, 2022).

On the other hand, regulatory changes and market events affecting institutional illiquid/concentrated instruments, such as those in the Peruvian capital markets, can be more significant. For instance, Sias (2004) and Coval (2007) highlight institutional herding and fire sales, where collective trades amplify stock price swings beyond fundamentals. Indeed, Coval (2007) shows that fire sales force institutions to liquidate assets simultaneously, creating contagion, excess comovement, and price distortions—revealing fragility in financial markets beyond fundamental values.

If we now turn to Latin America, the influence of private pension fund flows on asset prices, such as exchange rates, has been studied by Aldunate, Zhi, Larrain, & Sialm (2025). They analyzed the case of the retail firm "Felices y Forrados" and offered a series of recommendations to thousands of AFP affiliates over 10 years (2011-2021) to switch funds. Chile has a flexible switching rule that allows affiliates to request a switch between funds, facilitating the movement of thousands of affiliates over very short time frames. These multiple movements generate AFP flows that affect the FX spot, the banks that hedge forwards, and, therefore, the deviation of the CIP in Chile.

Additional studies, such as Chian & Ruiz (2020), analyze a Chilean regulatory-induced fire sale in which regulators banned cross-ownership among AFPs (pension funds). That rule forced AFP to sell off their equity stakes in other AFP-managed funds within a year. Evidence shows that AFPs' sales were shaped by portfolio overexposure and asset characteristics, confirming herding behavior and highlighting policy risks of concentrated institutional investments.

A related study by Cerda (2024) analyzes the impact of pension fund asset liquidation on long-term bond yields in Chile. The liquidation was driven by the approval of the COVID-19 withdrawal in 2020 and 2021. This study analyzes the fixed-income markets. Using autoregression analysis, the reduction in portfolio holdings impacts the ten-year Chilean government bond.

Carhuancho (2020) examines the effects of events and regulatory changes in Peru, focusing on the introduction of COVID-19 and its withdrawal. It addresses the impact on liquidity at the Lima stock exchange. The AFP type 3 fund is just one part of the model's explanation. The study found that, given the effects of COVID-19, the AFPs' type 3 withdrawals, returns, and stock volatility, the market's liquidity increased slightly.

So far, the methodological approach taken in this study aligns closely with the study events for Latin American markets. Diez (2024) analyzes Chile's pension fund's three withdrawals and their impact on Chilean capital markets. Using the event study methodology, it examines the effects of each announcement and pre-announcement discussion on the Chilean stock market. The document shows that simulated Chilean stock portfolios underperform relative to their predicted behavior based on capital market indicators and commodity prices.

In addition, for Argentina, Sandoval & Aquino (2025) analyze abnormal returns for the Merval index and its main sectors after the 2023 presidential election. Similarly, Rocha & Da Silva, using event studies, find evidence of the COVID-19 negative impact on the abnormal returns for airline sector in Colombia and Brazil.

3 Event Analysis: What happened during the event?

COVID-19 became a public issue on January 30th, 2020, after the World Health Organization (WHO) raised the alarm. By March 9th of the same year, the WHO declared COVID-19 a pandemic, and the Peruvian government declared a lockdown. After that, the situation worsened when the government declared a total lockdown on March 16th. The government announced several measures to counter the lockdown, including a PEN 380 bonus for vulnerable households (later increased to PEN 760). As time passed, one of the most salient proposals was the withdrawal of personal funds from pension funds.

3.1 1st Event (1st, 2nd, and 3rd Withdrawal)

By April 1st, the first withdrawal was approved by the Peruvian president under urgent decree 034-2020, which allowed a one-time withdrawal of up to PEN 2,000. At the beginning of the pandemic and the lockdowns, the SPBVL fell by -4.9% from March 16th to March 31st. During this time, the financial markets experienced significant levels of volatility, which required the use of non-conventional public policies, such as quantitative easing (Zhang, 2020) In the case of Peru, alternative measures included the reduction of the Central Bank interest rate from 2.25% to 0.25%, and programs like Reactiva Peru that allocated 30 million PEN in order to boost the restricted national economy.

Additionally, by April 14, 2020, the Peruvian government approved the second withdrawal of PEN 2,000 as a one-time withdrawal under Urgency Decree 038-2020. During this time, from the beginning of the lockdown on March 16th to the second week of the pandemic, Congress proposed withdrawing 25%; however, the Peruvian government demurred, arguing that such a measure would be detrimental to long-term public finances and was unnecessary given the previous 2 withdrawals approved.

Finally, the congress approved the third withdrawal under Law 31017 (April 29th), allowing the withdrawal of 25% of the funds accumulated to that point. This measure was unprecedented, as it was the first time a significant amount of funds was to be liquidated by the pension funds in such a short period. The event we are going to analyze actually starts with the discussion of the norm and continues through the announcement. The 1st and 2nd withdrawals are important; however, for our study, we are only considering the 1st event after the 3rd withdrawal.

The Figure 1 shows the evolution of the SP&BVL from February 20th until May 28th, with the dotted lines marking the key dates for the withdrawals.

The 1st withdrawal approval on March 29th is shown in green, the 2nd on April 14th in red, and the 3rd on April 29th in blue. Considering our chosen event, the market showed a positive trend before and

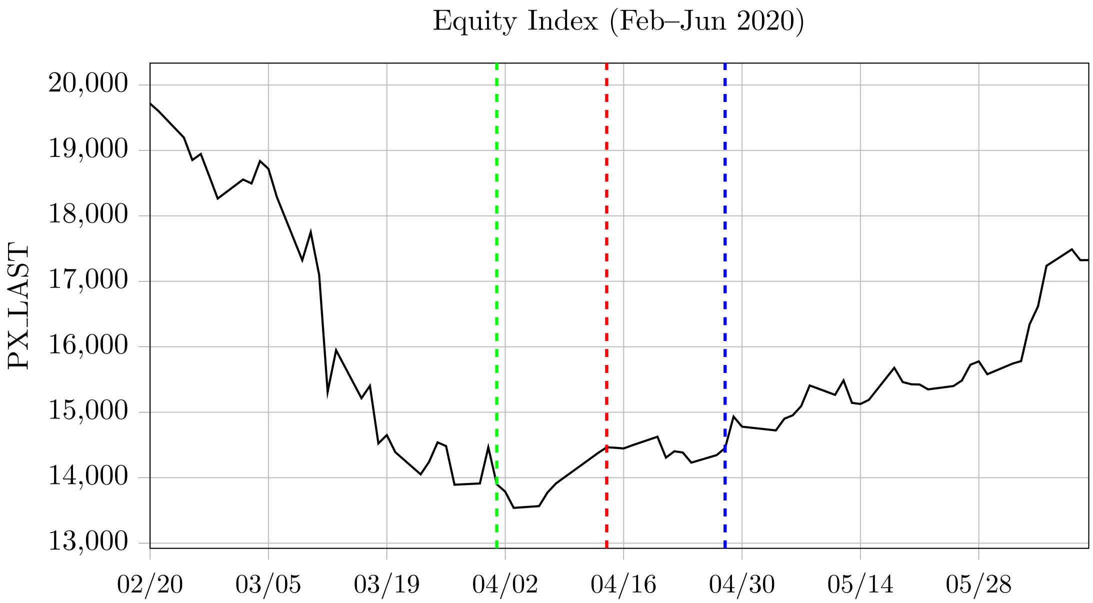

Figure 1: BVL Stock Market Index from Febraury 20, 2020 to June 13rd, 2020

after the 3rd withdrawal, increasing by 9.1% (+/- 30 days around the withdrawal). So, even considering the first withdrawal (green line), the subsequent trend was also positive. We believe this favorable trend aligns with the worldwide initiative to provide fiscal and monetary support, as well as with the rise of the S&P 500 by 18.7% during that time.

3.2 2nd Event (4th Withdrawal)

On November 18, 2020, the Peruvian Congress approved the fourth withdrawal under Law 31068, which authorized the extraction of up to 4 UIT (equivalent to 17,200 soles). This measure is estimated to have prompted withdrawals of roughly 9,016 million soles, necessitating substantial liquidation of AFP assets to meet demand. The approval occurred amid intense political instability following the impeachment of President Martín Vizcarra. During the brief and turbulent one-week administration of Manuel Merino, Congress advanced several highly populist measures, including this law. By then, months of strict lockdown had worsened the financial strain on households, and widespread discontent toward the AFP system created fertile ground for increasingly permissive—and politically expedient—proposals favoring large-scale pension withdrawals.

Figure 2 shows the evolution of the SP&BVL from October 6th until December 29th, with the dotted lines marking the key dates for the withdrawals.

From the graph, the red line represents the official announcement of the law on November 17th, and the blue line represents the pre-announcement on October 28th. As we focus on the announcement date

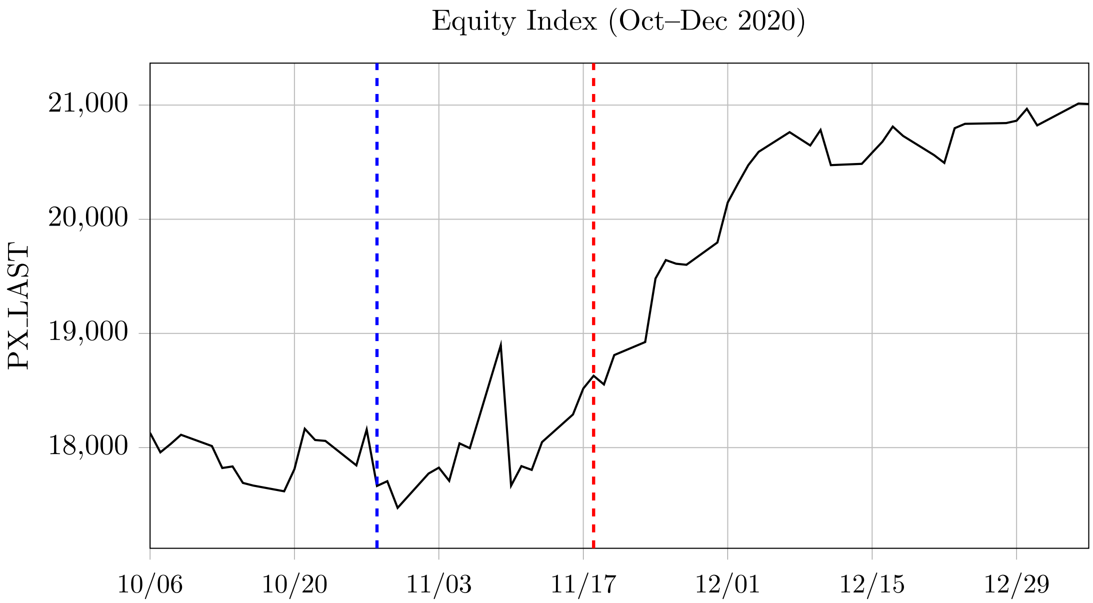

Figure 2: BVL Stock Market Index from October 6, 2020, to January 2, 2021

(blue line), the market increased by 17% over the 30 days before and after the withdrawal announcement, with the SP500 increasing by 8.2%. We believe the market rally after November 17th is due to political stabilization following the abrupt end of the Merino administration.

3.3 3rd Event (5th Withdrawal)

On May 7th, 2021, the Peruvian Congress approved the fifth withdrawal under Law 31192, authorizing up to 4 UIT (PEN 17,200) per contributor. The measure is estimated to have triggered withdrawals amounting to roughly S/ 32.2 billion, thereby forcing an extraordinary liquidation of AFP portfolio assets. Although enacted during the transitional administration of President Francisco Sagasti, the government explicitly opposed the initiative, arguing that it threatened fiscal sustainability and undermined the institutional coherence of the pension system. Unlike the emergency-driven logic of the earlier withdrawals, this fifth withdrawal signaled the onset of a structural rupture in the regulatory framework governing pension-fund access, extending far beyond the exceptional economic and political conditions that had justified the earlier rounds of withdrawals.

Figure 3 shows the evolution of the SP&BVL from March 23rd until June 15th, with the dotted lines marking the key dates for the withdrawals. The graph shows the blue line representing the preliminary announcement on April 16th, while the red line denotes the formal enactment of the law on May 7th. When examining the announcement date (blue line), the market declined by 6.1% over the 15 days surrounding the withdrawal debate.

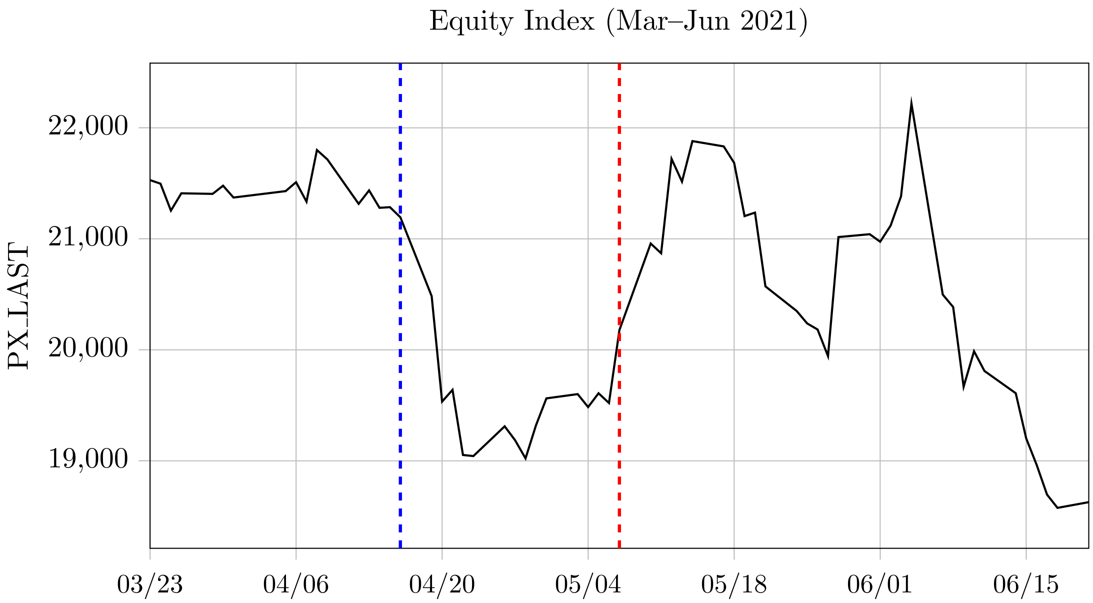

Figure 3: BVL Stock Market Index from March 23, 2021, to June 20, 2021

3.4 4th Event (6th Withdrawal)

On May 21, 2022, the Peruvian Congress approved the fifth withdrawal under Law 31478, authorizing the extraction of up to 4 UIT (equivalent to PEN 17,200). This law is estimated to have triggered withdrawals amounting to roughly PEN 21,994 million, thereby potentially forcing substantial liquidation of AFP-managed pension fund assets.

The Peruvian capital markets were restive ahead of the sixth round of pension fund withdrawals, given the now-evident impact that such measures were expected to have on local stocks. As the following graph shows, from April 5 to June 28th, the SP&BVL Index declined, also pulled down by the contractionary monetary policy following the significant stimulus during the COVID-19 lockdowns:

Figure 4 shows the red line marking the official announcement of the law, while the blue line corresponds to the pre-announcement. Focusing on the pre-announcement date (blue line), the market fell by 17.5% over the 15-day window surrounding the discussion of the withdrawal. Over the subsequent 15 days, the index registered an additional 0.4% decline after the legislators approved the law.

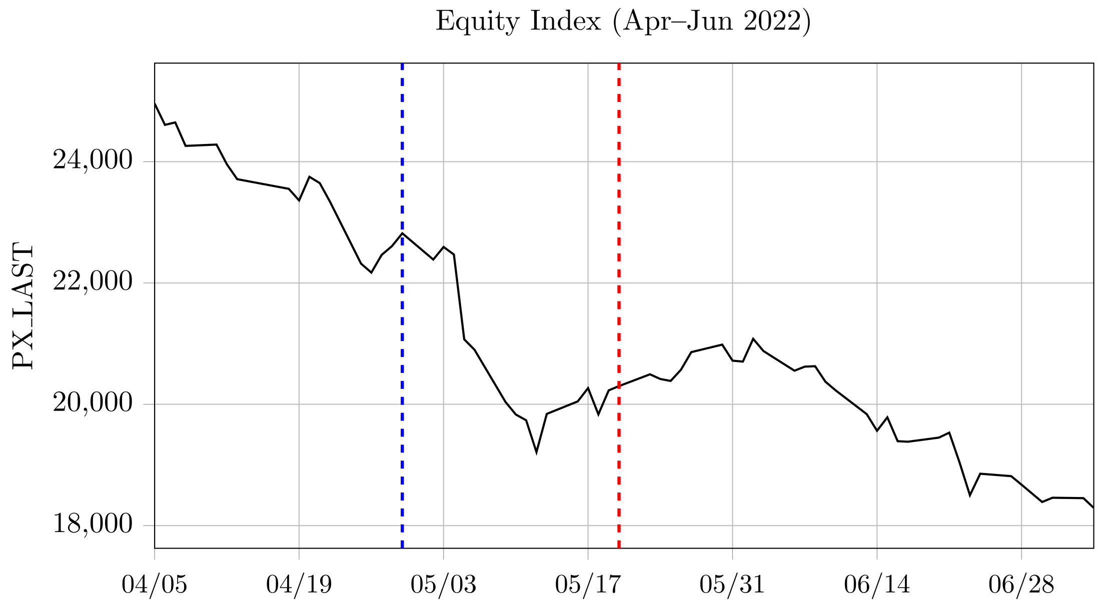

Figure 4: BVL Stock Market Index from April 04, 2022, to July 1st, 2022

3.5 5th Sector (7th Withdrawal)

The seventh withdrawal was approved on April 17, 2024, under Law 32002, which authorized the extraction of up to 4 UIT (PEN 17,200). This law is estimated to have triggered withdrawals of roughly PEN 34,000 million, thereby requiring a potential liquidation of AFP-managed portfolio assets. The proposal had been under debate in Congress for two weeks before it was approved.

Considering the seventh withdrawal, Figure 5 spans the period from March 1st to May 24th. The red line marks the formal announcement, whereas the blue line identifies the start of the congressional debate on March 24th. Over the 15 days following the beginning of the discussion (blue line), the stock market index contracted by 7.6%, suggesting an association with the discussion. By contrast, over the 15 days following the official announcement (red line), the index rose by 8.4%, effectively restoring price levels to those observed before the debate began.

3.6 Summmary of Events

Following the identification of the seven extraordinary AFP withdrawal events summarized in Table 1, each episode constitutes a distinct exogenous shock to the Peruvian financial market. The events represent policy-driven interventions that directly affected the liquidity positions of private pension funds, compelling portfolio rebalancing and potential asset sales. The analysis focuses on the impact of these withdrawals on a selected group of equities traded on the Lima Stock Exchange (BVL), which were

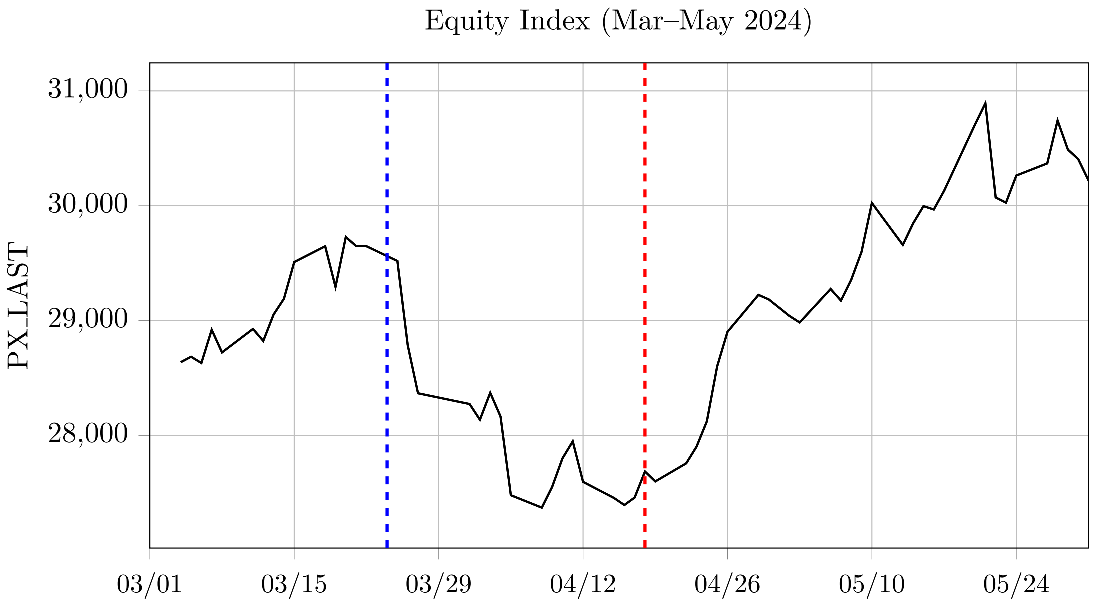

Figure 5: BVL Stock Market Index from March 01, 2024, to May 29, 2024

consistently held by AFPs and thus most exposed to liquidation pressures. Event windows are carefully delimited around the official announcement and implementation dates of each withdrawal to capture the immediate market reaction while controlling for potential overlap between successive episodes.

Table 1: Summary of Extraordinary AFP Withdrawal Events (2020-2024)

Event #	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Withdrawal Law / Decree	DU No. 034-2020	DU No. 038-2020	Law No. 31017	Law No. 31068	Law No. 31192	Law No. 31478	Law No. 32002
Announcement Date	Apr 30 2020	Jul 8 2020	Dec 4 2020	May 20 2021	May 20 2022	May 18 2023	May 20 2024
Approx. Amount Released (PEN bn)	$\approx$2.9	$\approx$2.1	$\approx$19.6	$\approx$9.0	$\approx$31.2	$\approx$21.9	$\approx$34.0
Estimation Window	-120 to -31	-120 to -31	-120 to -31	-120 to -31	-120 to -31	-120 to -31	-120 to -31
Event Window	-15 to $+15$	-15 to $+15$	-15 to $+15$	-15 to $+15$	-15 to $+15$	-15 to $+15$	-15 to $+15$
Post-Event Window	$+15$ to $+30$	$+15$ to $+30$	$+15$ to $+30$	$+15$ to $+30$	$+15$ to $+30$	$+15$ to $+30$	$+15$ to $+30$
Key Context / Notes	First withdrawal: First PEN 2,000 withdrawal at the beginning of the lockdowns.	Second withdrawal: Second PEN 2,000 withdrawal as part of the lockdown decrees.	Third withdrawal: Withdrawal of 25% of pension fund accounts.	Fourth withdrawal: Part of the initiatives from a transitional government.	Fifth withdrawal: This 4 UIT withdrawal marked the beginning of the pension fund's institutional disruption.	Sixth withdrawal: 4 UIT withdrawal and the beginning of the debate over the system sustainability.	Seventh withdrawal: 4 UIT withdrawal and renewed debate on system sustainability.

Notes: This table summarizes the seven extraordinary AFP withdrawal episodes in Peru between 2020 and 2024. Dates correspond to the event dates ($t = 0$), defined as the first widely disseminated public milestone (e.g., formal publication and/or the start of the legislative debate), as discussed in the Event Analysis section. The "Approx. Amount Released" entries are headline, approximate magnitudes reported in official communications and secondary summaries; they should be interpreted as order-of-magnitude indicators rather than precise realized outflows[1].

The sample consists of fourteen BVL-listed firms characterized by high institutional ownership, continuous trading activity, and complete data availability on prices, trading volumes, market capitalization, and liquidity measures. These securities were selected based on their persistent inclusion in AFP portfolios since 2014 and their relevance within the main Peruvian market index. The selection criteria ensure that the sample represents the segment of the equity market most sensitive to AFP trading behavior while also guaranteeing the integrity and frequency of the data required for daily return analysis.

4 Data

4.1 Data Sources and Coverage

This section details the data used for the analysis. The primary sources for the analysis are Bloomberg data from January 2019 to December 2024, with a daily frequency. The variables to consider are the SP&BVL Index, the SP 500 Index, copper prices, Peruvian 5-year Credit Default Swaps (CDS), and the prices of 14 stocks listed on the Lima Stock Exchange (BVL). The 14 stocks are Aenza, Alicorp, Luz del Sur, Engie, Ferreycorp, Inretail, Minsur, Nexa, Unacem, and Volcan [2]

Additionally, the data for the event dates come from "El Peruano," which is the source for official norms. These data are available at a daily frequency for all; they are relatively liquid and have a proven record of reacting to public news (local and global).

On the other hand, with regard to the data considerations, the returns for days when the stock does not trade are set to zero. And the reference for all the dates is the SP&BVL, as it is the primary variable for the analysis. In addition, the total list of stocks to be considered is the complete set of local stocks held by the pension funds reported to the Superintendencia de Banca, Seguros y AFPS (SBS), from which we are selecting the stocks that have been historically (over the last 10 years) in the pension funds' holdings.

4.2 Event Identification

The selection of the five dates considered as ($t = 0$) primarily stems from their association with the initial discussions concerning the withdrawal. Each date and its corresponding event were previously examined in the earlier section. Specifically, the first event refers to the third withdrawal announcement date. The second, third, fourth, and fifth events correspond to the commencement of the fourth, fifth, sixth, and seventh withdrawals, typically occurring 15 days prior to their respective announcements.

4.3 Variable Construction

All of the variables considered for the estimations are expressed as returns. Where the daily logarithmic returns are $ln(P_{t+1}/P_t)$. Furthermore, the pre-estimation window is from -120 to -31 days before the

[2] They are listed as AENZAC1, ALIPE, BAPUS, BBVAC1, BUENAVC1, CPACASC1, ENGIEC1, FERREYCPE, INRETC1, LUSURC1, MINSURI1, NEXAC1, UNACEMC1, VOLCABC1.

event date, and the window for abnormal returns will consider the 15 and 30 days before and after the event.

The market capitalization variables (composed of various stocks) are the SP&BVL and the SP500. Additionally, to estimate abnormal returns, we construct a market-capitalization-weighted index.

4.4 Descriptive Statistics

This article analyzes 7 withdrawal events, 1 Index for the multifactorial analysis, and 14 firms for the event study. As well as 150 observations for the whole estimation, there are 120 observations for the pre-estimation window and 30 for the abnormal estimation window.

5 Methodology for the SP&BVL Index Estimation

5.1 Pre-Event Estimation

5.1.1 Multi-Factor Model (for the SP& BVL Estimation)

We model the relationship between the Lima Stock Exchange return and the S&P 500 return ($R_{\text{S\&P500},t}$), copper returns ($R_{\text{Copper},t}$), and CDS changes ($R_{\text{CDS},t}$), adapting the specification in Diez 2024 [3]. The 2nd equation simplifies the multifactor model by replacing the coefficients with θ to present the regression parameters.

$$R_{BVL,t} = \alpha + \beta_1 * R_{SP500,t} + \beta_2 * R_{Copper,t} + \beta_3 * R_{CDS,t} + \epsilon_t \qquad \text{(Multifactor)} \qquad (1)$$

$$R_{BVL,t} = \theta * R_t + \epsilon_t \qquad \text{(Residuals)} \qquad (2)$$

The OLS estimators for the pre-event estimation window are presented below, following MacKinlay 1997 and consistent with the regression-based exposition in Miller 2023.

[3] In the Chilean specification, the pension fund's quoted value (e.g., NAV) enters as an explanatory variable in place of the Chilean stock market index. Additionally, the 10-year sovereign yield is included as an additional control.

$$\hat{\theta} = (X^\top X)^{-1} X^\top R \qquad \text{(OLS estimator)} \tag{3}$$

$$\hat{\varepsilon} = R - X\hat{\theta} \qquad \text{(Residuals)} \tag{4}$$

$$\sigma^2_{\hat{\varepsilon}} = \frac{\hat{\varepsilon}^\top \hat{\varepsilon}}{T_0 - K} \qquad \text{(Error variance)} \tag{5}$$

$$\text{Var}[\hat{\theta}] = (X^\top X)^{-1} \sigma^2_{\hat{\varepsilon}} \qquad \text{(Variance of OLS estimator)} \tag{6}$$

5.2 Event Estimation

The abnormal return (AR) for the BVL Index t is defined as the difference between the actual return and the expected return under the multi-factor model. In this case, we consider the actual return and estimate it to be around the event window ($L_1 - T_1$ and $L_1 + T_2$). In the same equation, we also introduce the cumulative abnormal return (CARs), which is defined as the sum of the abnormal returns from the period τ_1 to τ_2 ($T_1 < \tau_1, \tau_2 < T_2$).

$$AR_{BVL,t} = R_{BVL,t} - \hat{\theta}X \qquad \text{(AR)} \tag{7}$$

$$CAR_{[t_1,t_2]} = \sum_{t=t_1}^{t_2} AR_t \qquad \text{(CARs)} \tag{8}$$

5.3 Hypothesis Identification

The principal hypothesis for this analysis is that "discussions of AFP withdrawals generate negative abnormal equity performance on the BVL Index," given that the main risk factors for BVL returns are the SP500 Index, copper prices, and CDS returns.

$$\mathbf{H_0} : CAR_{[0,+15]} \geq 0 \quad , \quad \mathbf{H_1} : CAR_{[0,+15]} < 0.$$

$$\text{Pre-trend check: } \mathbf{H_0} : CAAR_{[-15,-1]} = 0 \quad , \quad \mathbf{H_1} : CAAR_{[-15,-1]} \neq 0.$$

5.4 Individual Testing

5.4.1 Distributional Assumptions

Under the null hypothesis of no abnormal performance, the vector of abnormal returns in the event window, ε_i^*, is assumed to be normally distributed. With the variance-covariance matrix given by the sum of the disturbance variance and estimation error variance:

$$\varepsilon_i^* \sim N(0, V_i), \qquad \text{(Mean Distribution)} \tag{9}$$

$$V_i = I\sigma_{\varepsilon,i}^2 + X_i^*(X_i'X_i)^{-1}X_i^{*\prime}\sigma_{\varepsilon,i}^2 \qquad \text{(Variance Distribution)} \tag{10}$$

where X_i^* denotes the regressors in the event window.

5.4.2 T-Statistic

Next, we present the CAR variance ($\sigma^2(\tau_1, \tau_2)$) and the Standardized CAR ($SCAR(\tau_1, \tau_2)$). The CAR variance measures the daily deviation of the CAR over the period we analyze (0 to 15 days in our case), while the SCAR is a statistical test to determine whether the CAR differs from 0 during the event period. We are assuming, under the null hypothesis, that the CAR has a normal distribution with a mean of zero and variance $\sigma^2(\tau_1, \tau_2)$.

$$Var[C\hat{A}R(\tau_1, \tau_2)] = \sigma^2(\tau_1, \tau_2)) = \gamma' V_i \gamma, \qquad \text{(CAR Variance)} \tag{11}$$

$$C\hat{A}R(\tau_1, \tau_2) \sim N(0, \sigma^2(\tau_1, \tau_2))), \qquad \text{(Normal)} \tag{12}$$

$$SC\hat{AR}(\tau_1, \tau_2) = \frac{C\hat{A}R}{\sqrt{Var[C\hat{A}R(\tau_1, \tau_2)]}} \qquad \text{(T-Stat)} \tag{13}$$

6 Methodology 14 Stocks Estimation

6.0.1 Multifactor Model

This analysis considers a multifactor model that examines the relationship between 14 local stocks (each identified by i in the equation) and the Lima Stock Market return [4] [5].

$$R_{i,t} = \alpha + \beta_1 * R_{SP500,t} + \beta_2 * R_{Copper,t} + \beta_3 * R_{CDS,t} + \beta_4 * R_{BVL,t-1} + \beta_5 * R_{BVL,t} + \beta_6 * R_{BVL,t+1} + \epsilon_t \quad \text{(Multifac} \tag{14}$$

$$R_{i,t} = \theta * R_t + \epsilon_t \quad \text{(Residual} \tag{15}$$

The OLS estimators for the pre-event estimation window are presented below.

$$\hat{\theta}_i = (X_i^\top X_i)^{-1} X_i^\top R \quad \text{(OLS estimator)} \tag{16}$$

$$\hat{\varepsilon} = R_i - X_i\hat{\theta} \quad \text{(Residuals)} \tag{17}$$

$$\sigma^2_{\hat{\varepsilon}} = \frac{\hat{\varepsilon}_i^\top \hat{\varepsilon}}{L_1 - 2} \quad \text{(Error variance)} \tag{18}$$

$$\text{Var}[\hat{\theta}] = (X^\top X)^{-1} \sigma^2_{\hat{\varepsilon}} \quad \text{(Variance of OLS estimator)} \tag{19}$$

6.1 Event Estimation

The abnormal return (AR) for each stock i in the time t is defined as the difference between the actual return and the expected return under the market model. In this case, we are considering the actual price and estimated around the event window ($L_1 - T_1$ and $L_1 + T_2$). In the same equation, we also introduce the cumulative abnormal return (CARs), which are defined as the sum of the abnormal returns from the period τ_1 and τ_2 ($T_1 < \tau_1, \tau_2 < T_2$).

[4] Peruvian equity market is thin and highly concentrated, which makes construction of reliable factor like portfolios (e.g., SMB, HML, MOM) infeasible in many months and unstable over time.

[5] Even the multifactor model presents some challenges on the use of the general index. Some of the participants quotes heavily in Nyse (BVN, BAP, IFS).

$$AR_{it} = R_{i,t} - \hat{\theta} X_i \qquad \text{(AR)} \qquad (20)$$

$$CAR_{i,[t_1,t_2]} = \sum_{t=t_1}^{t_2} AR_{i,t} \qquad \text{(CARs)} \qquad (21)$$

6.2 Hypothesis Identification

The primary hypothesis of this study posits that discussions concerning AFP withdrawals exert a negative effect on abnormal equity returns within the 14 local stocks that AFPs, after controlling the BVL prediction.

$$\mathbf{H_0} : CAR_{[0,+15]} = 0; \qquad \mathbf{H_1} : CAR_{[0,+15]} < 0.$$

$$\text{Pre-trend check: } \mathbf{H_0} : CAAR_{[-15,-1]} = 0.$$

6.3 Individual Testing

6.3.1 Distributional Assumptions

Under the null hypothesis of no abnormal performance, the vector of abnormal returns in the event window, ε_i^*, is assumed to be normally distributed. With the variance-covariance matrix given by the sum of disturbance variance and estimation error variance:

$$\varepsilon_i^* \sim N(0, V_i), \qquad \text{(Mean Distribution)} \qquad (22)$$

$$V_i = I\sigma_{\varepsilon,i}^2 + X_i^*(X_i'X_i)^{-1}X_i^{*\prime}\sigma_{\varepsilon,i}^2 \qquad \text{(Variance Distribution)} \qquad (23)$$

where X_i^* denotes the regressors in the event window.

6.3.2 T-Statistic

Next, we present the CAR variance ($\sigma^2(\tau_1, \tau_2)$) and the Standardized CAR ($SCAR(\tau_1, \tau_2)$). The CAR variance measures the daily deviation of the CAR during the period we want to analyze (0 to 15 days for our case), while the SCAR is a statistical test to measure whether the CAR is different from 0 during the event period. We are assuming, under the null hypothesis, that the CAR has a normal distribution with mean zero and variance $\sigma^2(\tau_1, \tau_2)$.

$$Var[C\hat{A}R(\tau_1, \tau_2)] = \sigma^2(\tau_1, \tau_2)) = \gamma' V_i \gamma, \qquad \text{(CAR Variance)} \tag{24}$$

$$C\hat{A}R(\tau_1, \tau_2) \sim N(0, \sigma^2(\tau_1, \tau_2))), \qquad \text{(Normal)} \tag{25}$$

$$SC\hat{AR}(\tau_1, \tau_2) = I\sigma^2_{\varepsilon,i} + X_i^*(X_i'X_i)^{-1}X_i^{*\prime}\sigma^2_{\varepsilon,i} \qquad \text{(T-Stat)} \tag{26}$$

6.4 Aggregation Analysis

6.4.1 Aggregation Across Securities

When studying N securities around the same event date, we aggregate individual CARs into an average cumulative abnormal return:

$$\overline{CAR}(T_1, T_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(T_1, T_2). \tag{27}$$

Its variance is given by:

$$Var\big[\overline{CAR}(T_1, T_2)\big] = \frac{1}{N^2}\sum_{i=1}^{N} \sigma_i^2(T_1, T_2), \tag{28}$$

with $\sigma_i^2(T_1, T_2) = Var[CAR_i(T_1, T_2)]$.

6.4.2 Test Statistics for Portfolio-Level Effects

Two common test statistics are used:

(i) J1 test:

$$J_1(T_1, T_2) = \frac{\overline{CAR}(T_1, T_2)}{\sqrt{\widehat{\sigma}^2(T_1, T_2)}} \quad \sim N(0, 1). \tag{29}$$

(ii) J2 test (average of standardized CARs):

$$\overline{SCAR}(T_1, T_2) = \frac{1}{N}\sum_{i=1}^{N} SCAR_i(T_1, T_2), \tag{30}$$

$$J_2(T_1, T_2) = \sqrt{\frac{N(L_1 - 4)}{L_1 - 2}}\, \overline{SCAR}(T_1, T_2) \quad \sim N(0, 1). \tag{31}$$

Thus, the event study framework proceeds from the measurement of abnormal returns [Eq. (**??**)], to their aggregation into CARs, and finally to statistical tests J_1 and J_2 for detecting systematic abnormal performance.

7 Results for the SP&BVL Index Estimation

7.1 Pre-Event Window Estimation

We estimate the BVL Index using a multifactor model, in which most event variables are significant and exhibit high explanatory power. We are running regressions for each event (from April 2020 to March 2024). Those events are estimated to be between 31 and 150 days before the event date (L_0). We are regressing on the S&P 500, copper price, and CDS price.

To begin with, for the first and second events (April to October), we had periods heavily influenced by the COVID-19 pandemic, increased volatility in global markets, and the fiscal and monetary policies employed to counter the economic impact of lockdowns. From those events, the three factors are significant, except for the S&P 500 in the second event.

In addition to the coefficient analysis, we observe that the coefficients for the SP&500 return and the copper price are positive across all events. Yet, for the second event, the SP&500 coefficient is close to zero. In contrast, the CDS return coefficient is negative for all the events; what's more, the CDS is more overexpressed in the second event. In general, the coefficients have the expected sign.

Table 2: Regression Results by Event Date

	4/16/2020	10/28/2020	4/16/2021	4/29/2022	3/22/2024
alpha	0.000	0.000	0.001	**0.002****	0.001
p-val	0.67	0.74	0.13	0.03	0.27
SP500 Coef	**0.332****	0.088	**0.229****	**0.286****	**0.197****
p-val	0.00	0.32	0.02	0.19	0.03
Copper Coef	**0.127****	**0.240****	**0.208****	**0.288****	**0.175****
p-val	0.02	0.02	0.00	0.00	0.04
CDS Coef	**-0.041****	**-0.135****	-0.111	-0.020	-0.024
p-val	0.02	0.00	0.18	0.74	0.56
R^2	39.6%	38.2%	27.4%	26.3%	10.4%
N	120	120	120	120	120

Notes: Coefficients (and α) marked with ** are significant at the 5% level ($p < 0.05$).

We point out that the predictive power for the first and second (39.6% and 38.2%) is greater than for the remaining events, highlighting the importance of the CDS's significance in the analysis and in the pre-COVID sample we are taking.

Furthermore, the S&P500 and the copper price are significant for the third, fourth, and fifth events, while the CDS factor is not, but we will consider the factor as it contributes to the provision of information in the model.

Finally, with respect to the independent factor (α), it does not show pre-trends (coefficients are very close to zero), except for the 2022 event, which had an anticipatory effect of the withdrawal. The coefficient of determination for each event is between 10% and 40%, which is relevant considering the noise around the general index.

7.2 Event Window Estimation

The cumulative abnormal returns are significantly negative from day 1 to day 15 after the 3rd, 4th, and 5th events. In contrast, in the 1st and 2nd events, the cumulative abnormal returns are positive, but the t-statistics are not statistically significant. For instance, Figure 6 shows that there is a sharp decrease for the 4th and 5th events, which contrasts with the slight decline of the 1st and 2nd events.

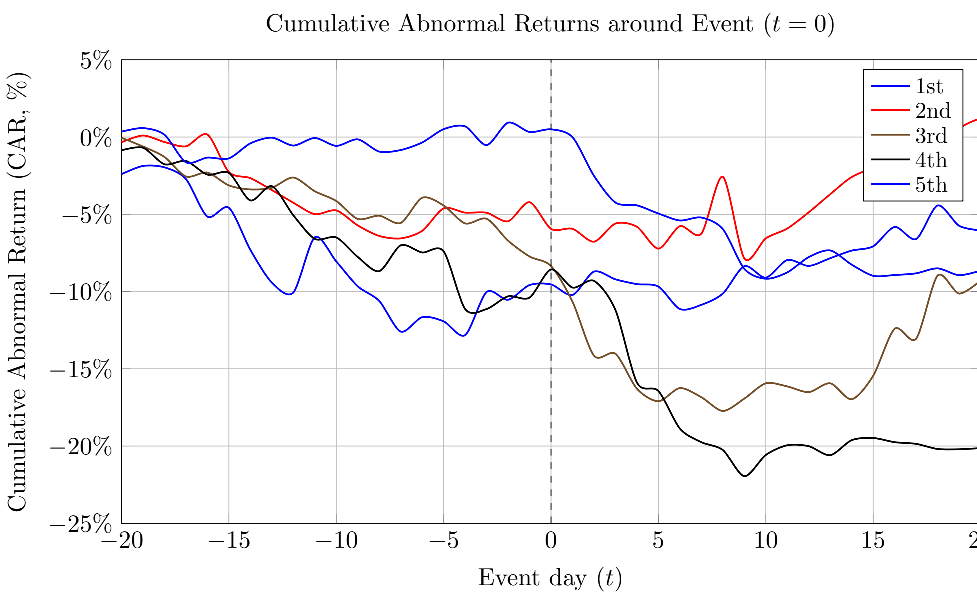

Figure 6: Cumulative abnormal returns (CAR) around the five withdrawal events. The vertical dashed line marks the event day ($t = 0$).

For days 1 to 30, as observed in Annex J, only the 4th and 5th events exhibit significant persistence beyond the month. While the 1st, 2nd, and 3rd events recover from their pre-level event shock. From a 15-day window to 1 day before the 1st and 4th events, we observed a clear pre-trend, evident even before the discussion began. Presumably, the trend was related to the COVID-19 lockdown, increased global stock market volatility, and leaks about the 1st and 4th events.

We must consider that the 4th and 5th events are economically significant, for context, the estimated CAR magnitudes (-12% and -10%) are large relative to broad-market moves over comparable horizons (S&P 500 30-trading-day returns [6]). Although we may have to review the negative pre-trend related to the cooling of monetary policy around the 4th event date, during which the Central Bank of Peru increased the reference rate from 3.5% to 4.5% from February 2022 to April 2022. However, around the 5th event, the reference rate was reduced from 6.25% to 6% from February 2024 to April 2024, giving a stronger signal on the effect of the last withdrawal.

On the whole, the 4th and 5th events exhibit a stronger market response than the 1st and 2nd events. A possible explanation is the different market and economic conditions between those periods, as well as the change in the institutional nature of the last two withdrawals on the Peruvian market. First, the first two events account for the volatility, the unprecedented shock, and the policies associated with COVID. Second, institutional changes since the 3rd event (5th withdrawal) have made the market wary of the withdrawal laws.

Table 3 illustrates the main results and the tests for CARs plots by each event $[-20, +20]$.

Table 3: Cumulative Abnormal Returns by Event and Window

ID	Date	Win.	L	CAR	SD	t
1	2020-04-16	+1,+15	15	**3%**	2%	1.24
1	2020-04-16	-1,+1	3	**0%**	1%	0.35
1	2020-04-16	-15,-1	15	**-5%****	2%	**-2.03**
2	2020-10-28	+1,+15	15	**4%**	4%	1.06
2	2020-10-28	-1,+1	3	**0%**	2%	-0.27
2	2020-10-28	-15,-1	15	**-4%**	4%	-1.09
3	2021-04-16	+1,+15	15	**-8%***	4%	**-1.93**
3	2021-04-16	-1,+1	3	**-4%****	2%	**-2.36**
3	2021-04-16	-15,-1	15	**-6%**	4%	-1.39
4	2022-04-29	+1,+15	15	**-12%*****	4%	**-2.90**
4	2022-04-29	-1,+1	3	**1%**	2%	0.34
4	2022-04-29	-15,-1	15	**-8%***	4%	**-1.94**
5	2024-03-22	+1,+15	15	**-10%*****	3%	**-2.90**
5	2024-03-22	-1,+1	3	**-1%**	2%	-0.62
5	2024-03-22	-15,-1	15	**2%**	3%	0.50

Notes: Two-tailed thresholds: * $|t| \geq 1.64$ (10%), ** $|t| \geq 1.96$ (5%), *** $|t| \geq 2.58$ (1%).

[6] 2.5% and -1.2% in a comparable period, 30 days after the 4th event (March 1, 2022) and the 5th event (March 27, 2024). Source: Bloomberg

7.3 Event Window Estimation General Testing

The J1 and J2 tests were used to evaluate whether the sum of the five events differs from zero. For instance, Table 4 presents the CARs test results before and after the event, highlighting CARs from day 1 to day 5 and day 15. Overall, the aggregated test indicate a statistically significant abnormal performance pattern around withdrawal events, conditional on the multifactor variables.

Table 4: Aggregate Cumulative Abnormal Returns Across Events

Win.	N	**CAR**	$J1$	$J2$	**sig.**$J1$	**sig.**$J2$
+1,+30	5	-13%	-1.09	-0.77		
+1,+20	5	-12%	-1.24	-0.91		
+1,+15	5	**-23%**	**-2.80**	**-2.40**	***	**
+1,+5	5	**-26%**	**-5.42**	**-4.99**	***	***
-5,-1	5	-2%	-0.44	0.04		
-15,-1	5	-21%	-2.58	-2.63	**	***
-20,-1	5	-32%	-3.40	-3.75	***	***
-30,-1	5	-43%	-3.71	-4.39	***	***

Notes: CAR aggregates results across five AFP withdrawal events. $J1$ and $J2$ are standardized test statistics using two variance estimators. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Shaded rows denote the primary post-event windows.

It is worth noting that the sum of CAR over the previous 15, 20, and 30 days is also statistically negative, suggesting a pre-trend even before the discussions began. In addition, as shown in Table 6, the sum of the CAR windows from -20 to 20 and -30 to 30 days is also significant, which may indicate a pre-trend before the event, particularly derived from the 4th and 5th events.

8 Results Multiple Stocks and Multiple Events

8.1 Pre-Event Window Estimation

To estimate multiple stocks, we use market-model regression analysis for the 14 stocks across the five events. We first analyze the significance of the regressions, the betas, then the coefficient of determination and the alphas, and finally how market conditions affect the parameters.

Overall, as shown in Annex C to G, the F-statistics are consistently significant for most of the events and the stock, which demonstrates reliability for the pre-estimation step. However, there are some stocks, like Engie for the 1st, 2nd, 3rd, and 5th events; and Aenza for the 2nd, 3rd, and 5th events, that have no significance. Additionally, for the 5th event (Annex G), half of the stocks are not significant in the estimation.

Furthermore, in most cases (51 of 70), the coefficients of determination show some explanatory power (more than 10%, given the lower trading levels in emerging markets). The main exceptions among the securities are the energy utilities (Engie and Luz del Sur, which have the lowest explanatory power among all regressions), the cement industrials (Pacasmayo and Unacem), and Minsur, which usually has very low liquidity. In contrast, the market model is more sensitive to stocks with high liquidity and market capitalization, such as Credicorp, Buenaventura, Ferreycorp, and BBVA.

Additionally, the pre-trend values of the estimated returns are close to zero. The exception is Minsur (stock with low liquidity), which had a significant positive pre-trend before the Volcan.

To conclude this regression results analysis, the explanatory power and significance of the second event's beta are greater than those of the other events. In contrast, the 5th event has lower explanatory power and more securities with lower significance, suggesting a disconnect between market movements and many stocks after the 4th withdrawal.

8.2 Event Window Estimation

We estimate the cumulative abnormal returns (CARs) for the 14 stocks (across all events) by forming two portfolios: an equally weighted portfolio and a value-weighted portfolio based on market capitalization. In addition, the estimation of the CARs for each event is in Annex H and Annex I.

The results shown in the Annex H indicate significant abnormal returns for the average of the securities' abnormal returns after the 3rd, 4th, and 5th events, which coincide with the statistically significant results for the multifactor model. As shown in Figure 7, only the second event shows a very slight increase, whereas the 1st, 3rd, 4th, and 5th events exhibit a steeper decline.

The most interesting finding, as shown in Annex J, was the contrast between the equally weighted portfolio's abnormal returns (Figure 7) and the market-weighted returns (Figure 8): the abnormal cumulative returns for the equally weighted portfolio are significantly negative on days 15 and 30 after the event, whereas the value-weighted returns are slightly positive (non-significant). The high weight of Buenaventura and Credicorp may explain the positive cumulative return for the value-weighted result.

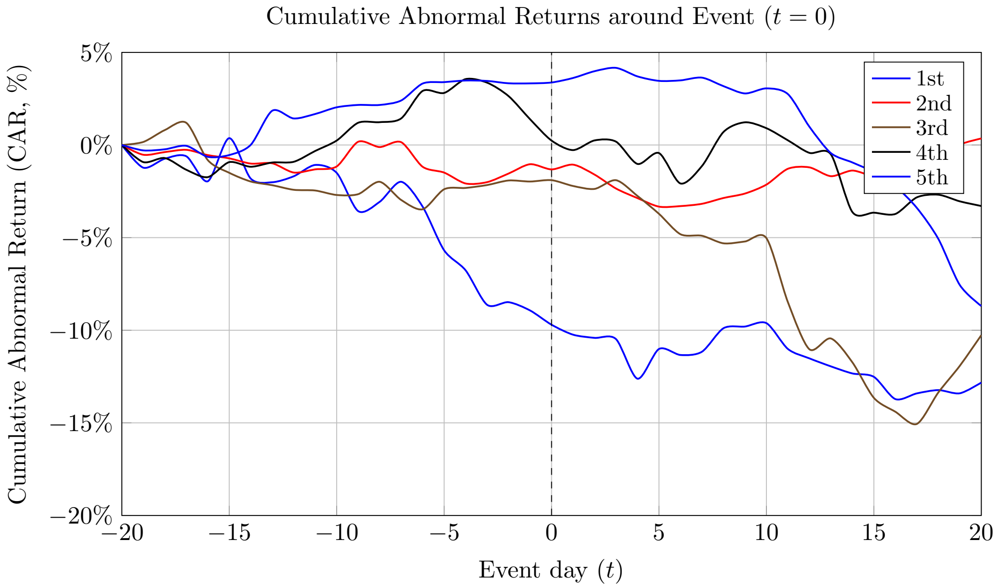

Figure 7: Cumulative abnormal returns (CAR) for the equally weighted portfolio around the five withdrawal events. The vertical dashed line marks the event day ($t = 0$).

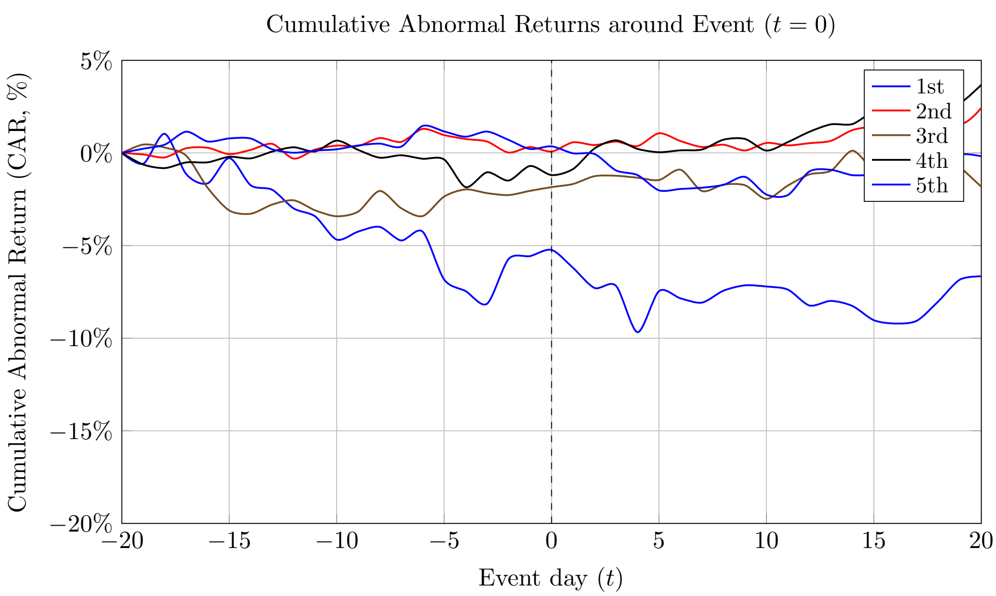

Figure 8: Cumulative abnormal returns (CAR) for the value weighted portfolio around the five withdrawal events. The vertical dashed line marks the event day ($t = 0$).

Table 5: Event-study CAR aggregation and joint tests for post-event windows (+1 to +k).

Window	N_{Events}	CARs	$J1\_Z$	$\overline{SCAR}$	$J2\_Z$	Sig_J1	Sig_J2	Weighting
+1,+15	5	-25%	-5.00	-2.49	-5.53	***	***	EW
+1,+20	5	-26%	-4.61	-2.56	-5.67	***	***	EW
+1,+30	5	-25%	-3.54	-1.82	-4.04	***	***	EW
+1,+5	5	-6%	-2.07	-0.90	-1.98	**	**	EW
+1,+15	5	0%	0.07	-0.15	-0.34			VW
+1,+20	5	5%	1.07	0.38	0.84			VW
+1,+30	5	4%	0.66	0.11	0.24			VW
+1,+5	5	-2%	-0.82	-0.59	-1.30			VW

Notes: The table reports portfolio-level cumulative abnormal returns (CARs) aggregated across $N_{\text{Events}} = 5$ AFP withdrawal events for post-event windows (+1 to +k). $J1\_Z$ tests whether the average CAR differs from zero using the estimated variance of the aggregated CAR, whereas $J2\_Z$ is based on the cross-sectional mean of standardized CARs ($\overline{SCAR}$) with a finite-sample adjustment. Asterisks indicate two-sided significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

9 Conclusion

Overall, the evidence suggests that AFP withdrawal episodes were not "just political noise" for the equity market. When we control for global and local risk factors (S&P 500, copper, and Peru's CDS), the SP&BVL exhibits sizeable negative abnormal performance in the later withdrawals, especially in 2022 and 2024, with CARs near 12% and 10% within +1 to +15 trading days. This pattern also appears in the 14-stock sample: the equally weighted portfolio reacts negatively and significantly, while the value-weighted portfolio is close to zero and mostly non-significant.

The difference between equally weighted and value weighted indices is relevant, as it captures the idea of a concentrated market where a few large-cap names dominate the index and can disguised stress in the broader set of AFP-held stocks. In other words, the average stock looks hit, but the weighted market can look fine.

At the same time, the pre-event windows are not always clean. Several events show negative CARs before $t = 0$, which is consistent with information leakage, anticipatory trading, or macro shocks (COVID in 2020; monetary tightening in 2022). Therefore, the causal story should be stated carefully: withdrawals likely added price pressure, but they were not the only moving part.

A natural extension is to add monthly AFP ownership concentration (or changes in holdings) to build an exposure measure and test whether more exposed firms experience larger CARs. Pairing this with liquidity and volume reactions would help distinguish fundamental repricing from forced-selling pressure. As a policy reflection, repeated withdrawals may increase the illiquidity and return effects in an already very thin market, worsening long-run financing conditions for local firms.

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A Annex A: Additional Figures

Table 6: Extended Cumulative Abnormal Returns Windows

window	**N_events**	**CAR_sum**	**J1_z**	**J2_z**	**sig_J1**	**sig_J2**
-1,+1	5	-5%	-1.28	-1.13		
-20,+20	5	-44%	-3.26	-3.27	***	**
-30,+30	5	-56%	-3.38	-3.63	***	***

Notes: The table reports aggregated CAR_sum across $N_{\text{events}} = 5$ events for extended symmetric windows around $t = 0$. $J1\_z$ and $J2\_z$ are joint test statistics, approximately $N(0, 1)$ under the null of zero abnormal performance. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Annex B: Additional Figures

Table 7: Average CARs and Test Statistics by Event and Window

event_id	**event_date**	**window**	**mean_car**	**sd_car**	**mean_scar**	**n_tickers**	**t_car**
1	4/16/2020	+1,+15	0%	6%	-13%	14	0.13
1	4/16/2020	+1,+30	2%	7%	37%	14	0.93
2	10/28/2020	+1,+15	2%	10%	20%	14	0.69
2	10/28/2020	+1,+30	0%	13%	4%	14	-0.01
3	**4/16/2021**	**+1,+15**	**-7%**	**10%**	**-155%**	**14**	**-2.55****
3	**4/16/2021**	**+1,+30**	**-8%**	**15%**	**-126%**	**14**	**-2.07****
4	**4/29/2022**	**+1,+15**	**-9%**	**12%**	**-132%**	**14**	**-2.70*****
4	**4/29/2022**	**+1,+30**	**-7%**	**13%**	**-77%**	**14**	**-2.03****
5	**3/22/2024**	**+1,+15**	**-13%**	**12%**	**-310%**	**14**	**-3.89*****
5	**3/22/2024**	**+1,+30**	**-8%**	**7%**	**-118%**	**14**	**-3.88*****

*, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

C Annex C: Pre-Estimation

Table 8: Model Estimation Results for the 1st Event

Ticker	R^2	F-Value	N	Const	β_{SP500}	β_{Copper}	β_{CDS}	$\beta_{\text{BVL},L1}$	β_{BVL}	$\beta_{\text{BVL},F1}$
AENZA	14%	0.009	121	0.00	0.16	-0.05	0.10	0.68	1.28	0.06
ALIPE	15%	0.006	121	0.00	-0.02	-0.04	0.04	0.08	0.53	-0.08
BAPUS	49%	0.000	121	0.00	0.36	-0.11	0.00	-0.16	1.22	0.03
BBVA	7%	0.181	121	0.00	0.14	0.05	-0.06	-0.06	0.04	-0.18
BUENAV	30%	0.000	121	0.00	-0.53	-0.31	0.04	0.12	1.61	0.17
CPACAS	10%	0.050	121	0.00	-0.31	-0.13	-0.01	0.48	0.24	0.33
ENGIE	3%	0.778	121	0.00	-0.05	0.01	0.00	-0.08	0.09	0.12
FERREYC	24%	0.000	121	0.00	0.37	-0.33	0.00	0.12	0.77	0.07
INRET	9%	0.073	121	0.00	0.54	-0.14	0.03	0.04	0.21	-0.20
LUSUR	11%	0.038	121	0.00	1.51	0.00	0.16	0.46	0.59	-1.22
MINSUR	10%	0.066	121	0.00	-0.27	0.15	-0.01	0.29	0.59	0.22
NEXA	7%	0.228	121	0.00	0.11	0.34	0.11	-0.12	1.08	-0.67
UNACEM	11%	0.040	121	0.00	-0.18	0.25	-0.01	0.20	0.43	0.18
VOLCAN	24%	0.000	121	0.00	0.41	0.72	-0.15	-0.17	1.44	-0.20

Note. For each ticker, the table reports the market-model regression over the pre-event estimation window ($N = 121$). R^2 and the F-value summarize fit and joint significance. Reported coefficients include the constant and factor loadings on SP500, Copper, CDS, and BVL leads/lags ($L1$, t, $F1$).

D Annex D: Pre-Estimation

Table 9: Model Estimation Results for the 2nd Event

Ticker	R^2	F-Value	N	Const	β_{SP500}	β_{Copper}	β_{CDS}	$\beta_{\text{BVL},L1}$	β_{BVL}	$\beta_{\text{BVL},F1}$
AENZA	23%	0.000	121	0.00	0.04	-0.23	0.01	-0.43	0.93	0.42
ALIPE	30%	0.000	121	0.00	0.19	-0.10	0.07	0.36	0.52	-0.10
BAPUS	65%	0.000	121	0.00	0.24	-0.14	0.00	-0.19	1.17	0.12
BBVA	55%	0.000	121	0.00	-0.10	0.17	-0.14	0.07	0.58	-0.30
BUENAV	40%	0.000	121	0.00	-0.39	-0.15	0.01	0.07	2.15	-0.26
CPACAS	17%	0.002	121	0.00	0.01	0.11	0.03	0.09	0.37	0.01
ENGIE	13%	0.013	121	0.00	-0.05	-0.01	0.02	0.12	0.16	-0.01
FERREYC	29%	0.000	121	0.00	0.03	0.05	0.00	0.11	0.83	0.31
INRET	24%	0.000	121	0.00	-0.09	-0.01	-0.03	0.08	0.50	0.30
LUSUR	16%	0.002	121	0.00	-0.12	-0.05	-0.12	0.10	0.31	0.09
MINSUR	13%	0.012	121	0.00	0.02	0.07	0.02	0.05	0.34	0.08
NEXA	39%	0.000	121	0.00	0.98	1.00	0.25	0.33	1.21	0.80
UNACEM	21%	0.000	121	0.00	-0.10	0.07	-0.03	0.17	0.56	-0.10
VOLCAN	37%	0.000	121	0.00	0.53	0.51	0.06	0.31	0.34	-0.15

Note. For each ticker, the table reports the market-model regression over the pre-event estimation window ($N = 121$). R^2 and the F-value summarize fit and joint significance. Reported coefficients include the constant and factor loadings on SP500, Copper, CDS, and BVL leads/lags ($L1$, t, $F1$).

E Annex E: Pre-Estimation

Table 10: Model Estimation Results for the 3rd Event

Ticker	R^2	F-Value	N	Const	β_{SP500}	β_{Copper}	β_{CDS}	$\beta_{\text{BVL},L1}$	β_{BVL}	$\beta_{\text{BVL},F1}$
AENZA	21%	0.000	121	0.00	0.19	-0.03	-0.01	-0.02	0.75	0.39
ALIPE	24%	0.000	121	0.00	-0.14	-0.05	-0.02	0.11	0.62	-0.02
BAPUS	75%	0.000	121	0.00	-0.20	-0.32	-0.01	-0.12	2.11	0.07
BBVA	21%	0.000	121	0.00	-0.08	0.08	-0.05	0.31	0.43	-0.40
BUENAV	32%	0.000	121	0.00	0.16	0.20	0.00	-0.25	0.99	-0.24
CPACAS	10%	0.050	121	0.00	-0.04	-0.09	-0.02	-0.05	0.34	-0.02
ENGIE	4%	0.510	121	0.00	0.00	0.02	-0.01	-0.03	-0.05	-0.08
FERREYC	14%	0.009	121	0.00	-0.10	0.04	0.01	0.08	0.48	0.01
INRET	11%	0.030	121	0.00	0.20	0.07	0.06	0.06	0.35	0.01
LUSUR	6%	0.328	121	0.00	0.15	0.11	0.05	0.09	0.33	0.00
MINSUR	7%	0.181	121	0.00	-0.25	0.22	-0.01	0.13	0.34	0.21
NEXA	12%	0.023	121	0.00	1.41	-0.22	0.43	0.33	0.60	-0.28
UNACEM	23%	0.000	121	0.00	-0.08	-0.08	-0.04	0.24	0.67	-0.28
VOLCAN	21%	0.000	121	0.00	0.22	0.19	-0.16	-0.27	0.49	0.01

Note. For each ticker, the table reports the market-model regression over the pre-event estimation window ($N = 121$). R^2 and the F-value summarize fit and joint significance. Reported coefficients include the constant and factor loadings on SP500, Copper, CDS, and BVL leads/lags ($L1$, t, $F1$).

F Annex F: Pre-Estimation

Table 11: Model Estimation Results for the 4th Event

Ticker	R^2	F-Value	N	Const	β_{SP500}	β_{Copper}	β_{CDS}	$\beta_{\text{BVL},L1}$	β_{BVL}	$\beta_{\text{BVL},F1}$
AENZA	17%	0.001	121	0.00	0.52	-0.17	0.01	0.02	0.79	-0.06
ALIPE	28%	0.000	121	0.00	-0.03	0.23	0.05	-0.07	0.59	0.13
BAPUS	74%	0.000	121	0.00	0.24	-0.13	0.07	0.09	1.46	-0.06
BBVA	30%	0.000	121	0.00	-0.33	0.02	-0.12	0.26	0.69	-0.19
BUENAV	45%	0.000	121	0.00	-0.68	-0.17	-0.05	0.10	1.64	0.20
CPACAS	20%	0.000	121	0.00	-0.09	-0.13	-0.09	-0.03	0.48	-0.17
ENGIE	5%	0.496	121	0.00	-0.11	0.02	-0.01	-0.07	0.02	0.00
FERREYC	27%	0.000	121	0.00	-0.26	0.05	0.04	-0.21	0.90	0.02
INRET	25%	0.000	121	0.00	-0.16	-0.04	0.00	0.04	0.70	-0.03
LUSUR	4%	0.622	121	0.00	0.06	0.18	0.09	0.06	0.03	-0.08
MINSUR	21%	0.000	121	0.01	0.15	0.08	-0.11	-0.12	0.72	-0.22
NEXA	23%	0.000	121	-0.01	0.71	0.36	0.10	0.50	1.09	0.29
UNACEM	9%	0.094	121	0.00	0.13	-0.08	-0.02	0.04	0.34	-0.12
VOLCAN	22%	0.000	121	0.00	-0.40	0.37	0.00	0.15	0.88	0.04

Note. For each ticker, the table reports the market-model regression over the pre-event estimation window ($N = 121$). R^2 and the F-value summarize fit and joint significance. Reported coefficients include the constant and factor loadings on SP500, Copper, CDS, and BVL leads/lags ($L1$, t, $F1$).

G Annex G: Pre-Estimation

Table 12: Model Estimation Results for the 5th Event

Ticker	R^2	F-Value	N	Const	β_{SP500}	β_{Copper}	β_{CDS}	$\beta_{\text{BVL},L1}$	β_{BVL}	$\beta_{\text{BVL},F1}$
AENZA	1%	0.982	121	0.00	0.25	-0.03	0.07	0.06	-0.27	0.24
ALIPE	6%	0.331	121	0.00	-0.25	-0.01	0.01	0.13	0.20	0.11
BAPUS	63%	0.000	121	0.00	0.32	-0.05	0.05	-0.11	1.55	0.16
BBVA	18%	0.001	121	0.00	-0.13	0.12	-0.04	0.16	0.29	0.03
BUENAV	63%	0.000	121	0.00	-0.09	-0.23	0.13	0.53	2.32	-0.21
CPACAS	6%	0.276	121	0.00	0.30	-0.03	0.06	0.28	-0.07	0.24
ENGIE	5%	0.388	121	0.00	0.11	-0.02	0.04	0.07	-0.01	0.08
FERREYC	5%	0.466	121	0.00	-0.23	0.02	-0.08	-0.01	0.21	-0.17
INRET	13%	0.015	121	0.00	0.07	0.03	0.04	-0.12	0.27	0.11
LUSUR	3%	0.726	121	0.00	0.11	-0.02	-0.02	-0.07	0.06	-0.05
MINSUR	8%	0.138	121	0.00	-0.11	-0.10	-0.01	-0.27	0.42	0.06
NEXA	9%	0.079	121	0.00	0.19	0.07	-0.02	-0.12	0.51	0.38
UNACEM	3%	0.804	121	0.00	-0.14	0.04	0.00	0.03	0.19	-0.07
VOLCAN	14%	0.007	121	0.00	0.01	0.25	0.15	0.09	0.67	-0.08

Note. For each ticker, the table reports the market-model regression over the pre-event estimation window ($N = 121$). R^2 and the F-value summarize fit and joint significance. Reported coefficients include the constant and factor loadings on SP500, Copper, CDS, and BVL leads/lags ($L1$, t, $F1$).

H Annex H: Pre-Estimation

Table 13: Results CARs

Window	N_{Events}	CAR_SUM	$J1\_Z$	$\overline{SCAR}$	$L1$	$J2\_Z$	Sig_J1	Sig_J2	Weighting
+1,+15	5	-25%	-5.00	-2.49	120	-5.53	***	***	EW
+1,+20	5	-26%	-4.61	-2.56	120	-5.67	***	***	EW
+1,+30	5	-25%	-3.54	-1.82	120	-4.04	***	***	EW
+1,+5	5	-6%	-2.07	-0.90	120	-1.98	**	**	EW
-1,+1	5	-4%	-1.98	-0.92	120	-2.05	**	**	EW
-15,-1	5	-2%	-0.35	-0.15	120	-0.34			EW
-20,+20	5	-37%	-4.51	-2.39	120	-5.31	***	***	EW
-20,-1	5	-8%	-1.47	-0.70	120	-1.56			EW
-30,+30	5	-38%	-3.86	-1.95	120	-4.32	***	***	EW
-30,-1	5	-12%	-1.66	-0.82	120	-1.82	*	*	EW
-45,+45	5	-45%	-3.67	-1.72	120	-3.82	***	***	EW
-5,-1	5	-6%	-2.01	-1.06	120	-2.34	**	**	EW
+1,+15	5	0%	0.07	-0.15	120	-0.34			VW
+1,+20	5	5%	1.07	0.38	120	0.84			VW
+1,+30	5	4%	0.66	0.11	120	0.24			VW
+1,+5	5	-2%	-0.82	-0.59	120	-1.30			VW
-1,+1	5	1%	0.29	0.06	120	0.14			VW
-15,-1	5	-5%	-1.06	-0.63	120	-1.40			VW
-20,+20	5	-3%	-0.39	-0.39	120	-0.86			VW
-20,-1	5	-8%	-1.62	-0.96	120	-2.12		**	VW
-30,+30	5	1%	0.15	-0.20	120	-0.45			VW
-30,-1	5	-3%	-0.44	-0.41	120	-0.91			VW
-45,+45	5	6%	0.59	0.05	120	0.12			VW
-5,-1	5	-2%	-0.99	-0.47	120	-1.03			VW

Note. For each ticker, the table reports the market-model regression over the pre-event estimation window ($N = 121$). R^2 and the F-value summarize fit and joint significance. Reported coefficients include the constant and factor loadings on SP500, Copper, CDS, and BVL leads/lags ($L1$, t, $F1$).

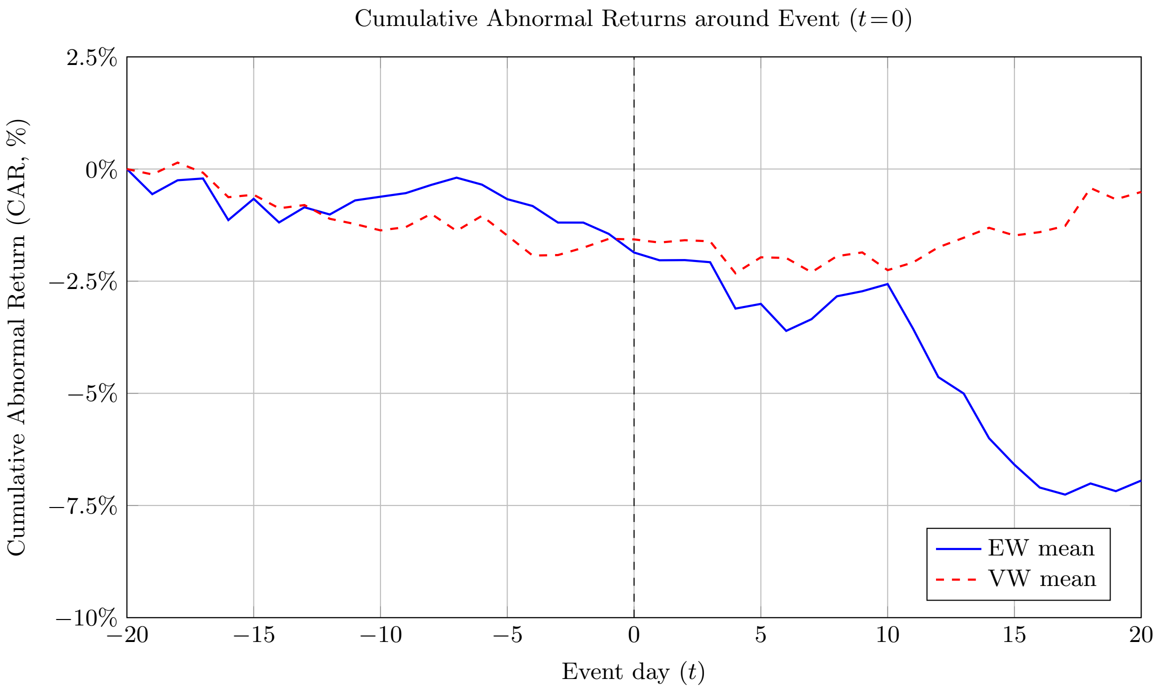
I Annex I: CARs

Table 14: Estimation Results

Event	Window	CAR_EW	SD_CAR_EW	t-SCAR_EW	CAR_VW	SD_CAR_VW	t-SCAR_VW
1	+1,+15	-3%	2%	-1.68	-4%	1%	-2.82***
1	+1,+20	-3%	2%	-1.61	-1%	2%	-0.86
1	+1,+30	2%	3%	0.77	-3%	2%	-1.67
2	+1,+15	0%	3%	-0.12	1%	3%	0.51
2	+1,+20	2%	3%	0.51	2%	3%	0.78
2	+1,+30	-1%	4%	-0.32	5%	4%	1.22
3	+1,+15	-13%	2%	-6.00***	1%	2%	0.59
3	+1,+20	-9%	2%	-3.59***	0%	2%	0.03
3	+1,+30	-8%	3%	-2.76***	0%	2%	0.16
4	+1,+15	-4%	2%	-1.64	3%	2%	1.79
4	+1,+20	-4%	3%	-1.28	5%	2%	2.20**
4	+1,+30	-6%	3%	-1.87*	6%	3%	2.04**
4	-5,-1	-1%	1%	-1.09	0%	1%	-0.34
5	+1,+15	-5%	2%	-3.04***	-2%	2%	-0.84
5	+1,+20	-12%	2%	-6.80***	-1%	2%	-0.24
5	+1,+30	-11%	2%	-4.93***	-3%	3%	-1.21

Notes: t-SCAR denotes the standardized CAR test statistic. Asterisks indicate two-sided significance based on $|t|$ cutoffs: * $p < 0.10$ ($|t| \geq 1.645$), ** $p < 0.05$ ($|t| \geq 1.96$), *** $p < 0.01$ ($|t| \geq 2.576$). $N_\sigma = 120$ for all rows.

J Annex J: Additional Figures



Notes: The figure plots cumulative abnormal returns (CARs) from $t = -20$ to $t = +20$, where $t = 0$ is the event day (vertical dashed line). EW_Mean is the equally weighted average CAR across securities, whereas VW_Mean is value weighted by market capitalization. Values are expressed in percent.