Are regime changes always bad economics? Evidence from daily financial data

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Abstract

We examine the relationship between political instability and daily returns of national stock indices in every country that experienced a coup, assassination, or resignation for which daily data is available. A common hypothesis is that political instability discourages investment and reduces economic growth. By contrast, we find that while financial volatility increases dramatically following "irregular" regime changes, different types of regime change have disparate effects on stock returns. We use daily financial data and a constant mean return event study model to show that abnormal returns following resignations are large and positive (4%), while abnormal returns following assassinations are negative and smaller in magnitude (2%). The impact of coups tends to be negative (2%), but some events result in positive abnormal returns of 10% or more. We also find that volatility increases during times of protest preceding resignations, but that no clear directionality is present. We therefore find that the expected direction and magnitude of abnormal returns is dependent on the type of political event and its expected impact on economic policy.

1 Introduction

The image of a coup or popular uprising ousting an autocratic ruler and installing a democratic government is an evocative one. However, both recent events and prior research suggest that coups rarely lead to democracy. In the wake of the Arab Spring - in which rulers were deposed in four countries and major protests occurred in six more - only Tunisia ultimately transitioned to democracy. These results are in line with prior research that claims that in autocracies coups rarely lead to democratization, and in democracies they cause instability (Derpanopoulos, Frantz, Geddes, & Wright 2016; Marinov & Goemans 2014; Powell & Thyne 2011; Thyne & Powell 2016; Varol 2011).

Of course, coups and other regime changes not only impact a country's political environment but its economy as well. For instance, investors, multinational firms, development agencies, and aid organizations, rank political risk as a top consideration when making investment decisions in emerging markets. Common rationales are that unstable governments act myopically and adopt inefficient policies (Devereux & Wen 1998; Svensson 1998)² and that policy uncertainty depresses business activity (Baker, Bloom, & Davis 2016). Such sentiments are supported by empirical research that suggests political instability—as measured by regime change frequency or political violence—is negatively correlated with investment, financial development, and GDP growth in cross country regressions (Aisen & Veiga 2013; Alesina, Özler, Roubini, & Swagel 1996; Alesina & Perotti 1996; Fosu 1992; Jong-A-Pin 2009; Roe & Siegel 2011) and that the variance of stock market returns increases in response to economic policy uncertainty (Jensen & Schmith 2005; Leblang & Mukherjee 2005; Liu & Zhang 2015).

However, such hypotheses are often overly simplistic. Not all political instability is equivalent - resignations, assassinations, and coups are all examples of regime changes, but may have disparate effects on financial returns. Resignations typically occur when an unpopular leader steps down and may signal the coming of a more effective leader. Assassinations are not always related to the effectiveness of a leader, can occur seemingly at random, and the

¹In the 2013 Multilateral Investment Guarantee Agency (MIGA) World Investment and Political Risk (2013) report (the last report published), executives of multinational enterprises (MNEs) ranked political risk as the second most important constraint for foreign direct investment (FDI) in developing countries over the next three years (after macroeconomic instability). In World Investment and Political Risk (2011) and World Investment and Political Risk (2012), political risk was ranked the most important constraint for FDI in developing countries - even greater than macroeconomic instability. The types of political risk of most concern to investors in developing countries (ranked in order of importance) were 1) adverse regulatory changes, 2) breaches of contract, 3) transfers and convertibility restrictions, 4) civil disturbances, 5) non-honoring of government guarantees, 6) expropriation nationalization, 7) terrorism and 8) war.

²Svensson (1998) argues that governments are less likely to invest in the legal system and the protection of property rights when political uncertainty is high. Similarly, Devereux and Wen (1998) propose a model in which political instability causes governments to leave fewer assets to their successors which forces them into increasing capital taxes. The knowledge of future taxation then causes the private sector to reduce current investment which reduces future output.

successor to the assassinated leader may be unclear. Coups can occur in the name of democracy or autocracy, and in general, signal relative weakness in the current political system. Further, political instability may be seen as a positive event if the current regime is regarded as strongly anti-business or anti-global. Alesina et al. (1996) take the possibility of a new government adopting better economic policies seriously, but argue that the negative effects of uncertainty dominate the positive effects of coups staged by pro growth factions. Likewise, Londregan and Poole (1990), find that coups have no impact on economic growth and hypothesize that this may because there is a bimodal distribution of coups, some of which enhance growth and others which restrict it.

In this study, we examine the impact of "irregular" regime changes and public protests on economic performance and remain agnostic about the direction of the effect. In contrast to the aforementioned cross country studies, we conduct our analysis using daily financial data. Market expectations in the form of stock market returns are therefore used as an indicator of whether the market views different types of potentially destabilizing political events as "good" for economic growth. The advantage of this event study approach is that it allows us to use time-series variation in stock returns to estimate treatment effects and mitigate the endogeneity problems that are nearly ubiquitous in cross country regressions.³

We find that financial volatility increases dramatically following (and just before) coups d'etat, assassinations, and resignations. However, unlike the previously mentioned studies, we find that these irregular regime changes have disparate effects on the direction of stock returns. Abnormal returns following resignations are large and positive (4%) while abnormal returns following assassinations are negative and smaller in magnitude (2%). The impact of coups tends to be negative (2%), but some events result in positive abnormal returns of 10% or more.

³A growing body of work uses event studies to assess political phenomenon. For example, political events have been used to estimate the effect of political connections on firm value (e.g. Faccio 2006; Fisman 2001; Goldman, Rocholl, & So 2009). Studies in "forensic economics" have used abnormal returns from political events to locate or examine transactions such as insider trading (Dube, Kaplan, & Naidu 2011), illegal arms trading (DellaVigna & La Ferrara 2010), and the impact of hostilities on the financial performance of diamond mining firms in Angola (Guidolin & La Ferrara 2007).

These findings are consistent with research that shows that "good coups" - coups that lead to democratization or economic liberalization - are not the norm and therefore on average coups should not be expected to lead to increased economic development and positive market returns (Derpanopoulos et al. 2016; Marinov & Goemans 2014; Powell & Thyne 2011; Thyne & Powell 2016; Varol 2011). However, while "good coups" may be the minority, regime changes that attempt to overthrow anti-business autocrats may be expected to result in positive abnormal returns as investors see little risk of a replacement government "worse" than the status quo.

Our main finding is therefore that the type of political event and its expected impact on economic policy determines the direction of abnormal returns. Events expected to lead to more stable governance, economic liberalization, or democratization (such as willful resignations and coups that overthrow protectionist or leftist autocrats) are associated with positive returns, while those that consolidate authoritarian rule, exacerbate poor economic policies, or merely increase policy uncertainty have the opposite effect.

2 Data

Political data are primarily drawn from the Center for Systemic Peace's (CSP) Polity IV Coup d'etat dataset and Coup d'etat Events handbook. The Coup d'etat dataset includes the date of 1) successful coups, 2) attempted coups, 3) plotted coups and 4) alleged coup plots. We focus on successful coups because it is difficult to classify failed coups.⁴ The one exception is that we separately study the failed coup attempt in Venezuela in April 2002 in which the President of Venezuela, Hugo Chavez, was removed from office for two days because it provides a natural experiment that allows us to estimate the impact of the forceful removal of a left-wing populist with a pro-business regime.

The Coup d'etat Events handbook also provides a list of 1) auto-coups⁵, 2) the ouster

⁴Needler (1966, p. 617) has even gone so far as to say that "the categories of coups that were aborted, suppressed, or abandoned melt into each other and into a host of other non-coup phenomena so as to defy accounting."

⁵Defined by Center for Systemic Peace as the "occurrence of subversion of the constitutional order by a

Table 1: Regime changes

Date	Country	Political Outcome
	Coups	
06/30/1970	Argentina	Autocracy to autocracy
03/22/1971	Argentina	Autocracy to autocracy
03/24/1976	Argentina	Democracy to autocracy
10/06/1976	Thailand	Anocracy to autocracy
10/20/1977	Thailand	Autocracy to anocracy
12/12/1979	South Korea	Autocracy to autocracy
02/23/1991	Thailand	Anocracy to anocracy
04/05/1992	Peru	Democracy to anocracy
10/12/1999	Pakistan	Democracy to autocracy
10/04/2002	Nepal	Democracy to autocracy
09/19/2006	Thailand	Democracy to anocracy
01/11/2007	Bangladesh	Democracy to autocracy
07/03/2013	Egypt	Anocracy to anocracy
05/22/2014	Thailand	Democracy to anocracy
	Failed coup	
04/11/2002	Venezuela	Democracy to democracy
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	Assassinations	
09/06/1901	United States	Democracy to democracy
11/22/1963	United States	Democracy to democracy
10/26/1979	South Korea	Autocracy to autocracy
10/31/1984	India	Democracy to democracy
02/28/1986	Sweden	Democracy to democracy
05/01/1993	Sri Lanka	Anocracy to anocracy
11/04/1995	Israel	Democracy to democracy
06/01/2001	Nepal	Democracy to democracy
	Resignations	
06/17/1982	Argentina	Autocracy to autocracy
02/25/1986	Philippines	Autocracy to democracy
12/06/1990	Bangladesh	Anocracy to anocracy
05/24/1992	Thailand	Anocracy to anocracy
04/18/1993	Pakistan	Democracy to democracy
11/05/1996	Pakistan	Democracy to democracy
06/30/1997	Turkey	Democracy to democracy
05/21/1998	Indonesia	Autocracy to anocracy
01/20/2001	Philippines	Democracy to democracy
12/20/2001	Argentina	Democracy to democracy
04/06/2004	Lithuania	Democracy to democracy
12/26/2004	Ukraine	Democracy to democracy
04/20/2005	Ecuador	Democracy to democracy
04/24/2006	Nepal	Autocracy to democracy
01/14/2011	Tunisia	Anocracy to anocracy

Notes: The Polity score is used to classify political outcomes as follows: autocracy = $-10 \le$ score ≤ -6 , anocracy = $-5 \le$ score ≤ 5 , and democracy = $6 \le$ score ≤ 10 .

ruling (usually elected) executive and the imposition of an autocratic regime."

of leadership by foreign forces, 3) the ouster of leadership by rebel forces, 4) assassinations of the executive and 5) resignations of the executive due to poor performance and/or loss of authority. Daily financial data is available for countries in categories 4 and 5, so we supplement the coups with assassinations and resignations to form a list of "irregular" regime changes. The resignations are those in which the ruling executive was coerced to resign due to poor performance, public discontent and popular demonstrations.

We further supplement the CSP data with leadership data from Archigos Version 4.1, which allows us to identify additional cases in which a "leader lost power through irregular means." Irregular transfers of power are those in which leaders do not leave office "in a manner prescribed by either explicit rules or established conventions." Nearly all removals by irregular means result from the threat or use of force (e.g. coups, revolts and assassinations).

A list of the political events in our dataset is shown in Table 1. Coups tend to have the largest impact on the level of democratization as a number of countries have subequently transitioned from democracies to anocracies or autocracies. On the other hand, neither assassinations or resignations have much of an impact on the level of democratization.

Financial data are from the Global Financial Data database, which includes the longest available time series of stock prices. We collect data on national equity indices and two global equity indices, the S&P/IFC Emerging Market Investable Composite and the Morgan Stanley Capital International (MSCI) World Index. The S&P/IFC index includes securities from emerging markets while the MSCI index includes securities from developed markets only. We collect stock index data on every country in which there was a coup or coup attempt, an assassination or failed assassination, or a forced resignation.⁶ The longest available daily time series for these stock indices are listed in Table 2.

To gain perspective on the relationship between irregular regime changes and the stock market, Figure 1 plots the absolute value of daily stock returns averaged across all events. Returns are for 250 trading days—approximately one calendar year—before and after regime

⁶The list of failed assassinations are from Jones and Olken (2009). Coup attempts are those in category 2 in the CSP Coup d'etat dataset.

Table 2: List of stock indices

Argentina Beunos Aires SE General Index Dec-66 Jan-17 Australia Australia ASX All Ordinaries Jan-58 Jan-17 Bangladesh Dhaka SE Index Jan-90 Jan-17 Canada Canada S&P/TSX 300 Composite Jan-76 Jan-17 Chile Santiago IGBC General Index Jan-92 Jan-17 Colombia Colombia IGBC General Index Jan-92 Jan-17 Ecuador Ecuador Bolsa de Valores de Guayaquil (BVG) Jan-92 Jan-17 Egypt Cairo SE Index Dec-92 Jan-17 Emerging Market S&P/IFC Emerging Markets Investable Composite Jul-95 Jan-17 Greece Athens SE General Index Oct-88 Jan-17 India Bombday SE SENSEX Apr-79 Jan-17 India Bombday SE SENSEX Apr-79 Jan-17 India Bombday SE Price Index Jan-95 Jan-17 Indonesia Jakarta SE Composite Index Jan-95 Jan-17 Inda Tel Aviv 100 Index May-87 Jan-17
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Southeast Asia Dow Jones Southeast Asia Index Jan-92 Jan-17
Spain Madrid SE General Index Aug-71 Jan-17
Sri Lanka Colombo SE All-Share Index Dec-84 Jan-17
Sweden Sweden OMX Affarsvarlden General Index Jan-80 Jan-17
Taiwan Taiwan SE Capitalization Weighted Index Jan-67 Jan-17
Thailand Thailand SET General Index Apr-75 Jan-17
Tunisia Tunisia SE Index Dec-97 Jan-17
Turkey Instanbul IMKB 100 Price Index Oct-87 Jan-17
Ukraine Ukraine PFTS OTC Index Jan-98 Jan-17
United Kingdom UK FTSE All-Share Index Nov-62 Jan-17
United States Dow Jones Industrial Average Feb-1885 Jan-17
Uruguay Bolsa de Valores de Montevideo Index Jan-08 Jul-16
Venezuela Dow Jones Venezuela Stock Index Jan-92 Jul-07
Venezuela Caracas SE General Index Jan-94 Jan-17
World MSCI World Price Index Jan-76 Jan-17
Zambia Lusaka SE Index Jan-02 Apr-06
Zambia Lusaka SE Index Jul-11 Jan-17

Notes: Standard errors are in parentheses. "Days to rebound" is the number of trading days following a negative stock return for the national stock index to return to pre-event level (it is calculated if the price decreases on the event day, not if the event day abnormal return is negative). Returns are inflation adjusted.

changes.

The absolute value of returns on the event day (trading day 0) are significantly larger than on any other day. In addition, the magnitude of returns begins increasing just before the event day and remains high for a short period after. This suggests that financial volatility increases during the days surrounding regime changes, although it does not provide any evidence on mean returns.

Section 3 tests these results more formally. It will first analyze coups, assassinations and resignations separately and determine whether they increase mean returns. It will then combine all irregular regime changes and estimate the effect of regime changes on the variance of returns.

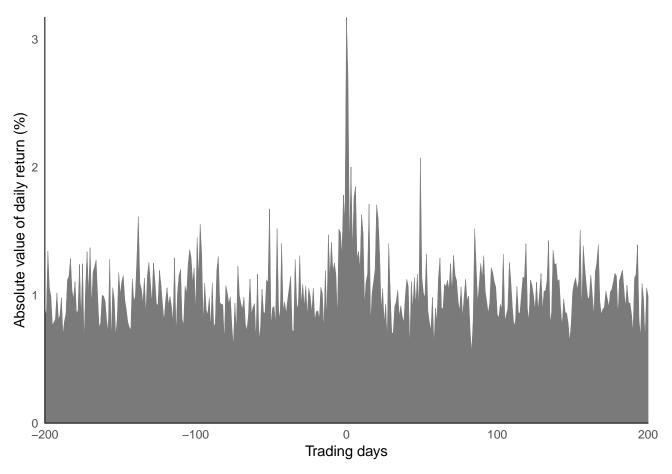


Figure 1: Absolute value of daily returns

3 Impact of Political Instability on Stock Returns

3.1 Abnormal Returns

We begin our analysis by studying the effect of irregular regime changes on stock returns. We follow the standard event study methodology as presented by, among others, MacKinlay (1997) and Campbell, Lo, and MacKinlay (1997). Normal performance is measured with a constant mean return model⁷,

$$R_{it} = \mu_i + \epsilon_{it},\tag{1}$$

where R_{it} is the logged return of national stock index i on trading day t and ϵ_{it} is the error term. We calculate abnormal returns (ARs), in an "event window" surrounding the date of each coup, $AR_{i\tau} = R_{i\tau} - \hat{\mu}_i$, where τ is a date in the event window, and $\hat{\mu}_i$ is estimated in an "estimation window" preceding the event window with Equation 1. We use a 41 day event window (i.e. 20 pre-event trading days, the event day, and 20 post-event trading days). The estimation window is the 250 trading days prior to the start of the event window. The abnormal returns are then used to generate cumulative abnormal returns (CARs) between event day τ_1 and event day τ_2 : $CAR(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}$.

We define the event date as the first trading day in which the market could have reacted to news of the event. For example, during the October 12, 1999 coup d'etat in Pakistan led by General Pervez Musharraf, the army announced that Prime Minister Nawaz Sharif had been dismissed after market hours at 10:15 pm. We code October 14th, the day in which the market re-opened, as the event day. When events occurred on weekends, we change the event date to the following Monday.

 $(0,\tau-1)$ is used to denote the τ -day period beginning with the event day and $(-1,\tau)$

⁷A constant mean return model is used instead of a market model in order to maximize the number of observations (plausible market indices such as the MSCI World Index and the S&P/IFC Emerging Markets Investable Composite Index only begin in 1976 and 1995 respectively). That said, results are insensitive to the use of a market model.

to denote the negative τ -day period beginning with the day prior to the event day. In other words, for cumulative abnormal returns prior to the event date, we aggregate backwards starting at the day of the event. For example, CAR(-1, -2) is the sum of the abnormal returns on event date -1 and event day -2.

We report abnormal returns separately for coups, assassinations and resignations because they may have distinct effects on stock returns. Standard errors and p-values are calculated using asymptotic t-statistics as in MacKinlay (1997).⁸

3.1.1 Coups

Table 3 shows abnormal returns for national stock indices both preceding and following coup d'etat. Table 3 contains all coups presented in Table 1 with the exception of the Argentinian coup of March 24, 1976 and the partial/failed Venezuelan coup attempt of 2002. The March 24, 1976 Argentinian coup is excluded from our analysis because the stock market remained closed from March 24 to April 5, 1976, or a period of twelve days. We later examine the Venezuelan coup attempt of 2002 in detail, but do not include it in the sample in Table 3 as it does not match our definition of a successful coup.

The average coup has a -2.1% event day AR. Event day ARs for the 1970 coup in Argentina, the 1991 coup in Thailand, the 1992 coup in Peru, and the 1999 coup in Pakistan are all negative and statistically different than zero. Moreover, all of these cases except Thailand have negative post-event CARs and pre-event CARs that are statistically indistinguishable from zero. In all of these cases, the coup in question either overthrew a democratically elected government or changed governance from one military ruler to another. The initial negative reaction followed by additional post-event negativity is consistent with the expected market reaction from a successful authoritarian coup followed by post-event consolidation of power.

⁸It is appropriate to use the standard normal distribution to calculate test statistics because the length of the estimation window is sufficiently long (250 trading days).

⁹Treating this twelve day period as a single day CARs results in a positive abnormal return of 58%, a fluctuation that seems qualitatively unreasonable.

Table 3: Abnormal returns following coups

		Post-Event CAR			Pre-Eve	Days to	
Country	Event Date	(0,0)	(0,6)	(0,19)	(-1,-7)	(-1,-20)	rebound
Argentina	06/08/1970	-1.919	-0.530	-2.011	0.247	4.728	204
		(0.949)	(2.510)	(4.243)	(2.510)	(4.243)	
Argentina	03/22/1971	0.925	14.294	24.218	0.131	0.274	
		(1.216)	(3.218)	(5.439)	(3.218)	(5.439)	
Thailand	10/06/1976	-0.541	0.837	0.731	0.001	0.713	3
		(0.639)	(1.691)	(2.859)	(1.691)	(2.859)	
Thailand	10/20/1977	-0.951	4.096	7.290	9.961	10.198	2
		(1.232)	(3.260)	(5.510)	(3.260)	(5.510)	
South Korea	12/12/1979	-1.784	-3.474	-24.465	-1.678	-6.187	418
		(1.152)	(3.047)	(5.150)	(3.047)	(5.150)	
Thailand	02/25/1991	-7.326	2.860	14.162	6.326	26.262	7
		(2.884)	(7.631)	(12.899)	(7.631)	(12.899)	
Peru	04/06/1992	-6.819	-5.814	-25.027	-2.075	-10.519	5
		(2.210)	(5.848)	(9.885)	(5.848)	(9.885)	
Pakistan	10/14/1999	-7.737	-9.431	-7.130	4.151	4.900	36
		(1.943)	(5.141)	(8.690)	(5.141)	(8.690)	
Nepal	10/04/2002	0.090	1.563	5.567	-1.014	-0.493	2
		(1.206)	(3.190)	(5.392)	(3.190)	(5.392)	
Thailand	09/19/2006	-0.481	-2.640	0.111	1.848	0.131	17
		(1.094)	(2.894)	(4.892)	(2.894)	(4.892)	
Bangladesh	01/11/2007	-0.320	10.351	14.883	-0.896	2.250	2
		(1.166)	(3.086)	(5.217)	(3.086)	(5.217)	
Egypt	07/03/2013	-0.346	5.169	7.144	6.776	-4.869	2
		(1.515)	(4.009)	(6.776)	(4.009)	(6.776)	
Thailand	05/23/2014	-0.571	2.800	4.591	2.350	-0.424	5
		(1.201)	(3.177)	(5.370)	(3.177)	(5.370)	
Mean		-2.137	1.545	1.543	2.010	2.074	58
		(0.424)	(1.121)	(1.896)	(1.121)	(1.896)	

Notes: Standard errors are in parentheses. "Days to rebound" is the number of trading days following a negative stock return for the national stock index to return to pre-event level (it is calculated if the price decreases on the event day, not if the event day abnormal return is negative). Returns are inflation adjusted.

Event day ARs are negative for all coups except the 1971 coup in Argentina and the 2002 failed coup d'etat attempt against Hugo Chavez (Figure 2). These results provide evidence that coups can in fact result in positive abnormal returns. While the 1971 Argentinian coup did result in another military leader, it did so while calling for free and democratic elections and replaced a government that had adopted extreme protectionist economic policies. In fact, by 1973 Argentina had transitioned to a democracy. The ultimately failed Venezuelan coup against Hugo Chavez replaced a left-wing populist government with a new pro-business

 $^{^{10}}$ Based on Center for System Peace Polity IV polity score of 6. Values of 6-10 are defined as democracies.

president.

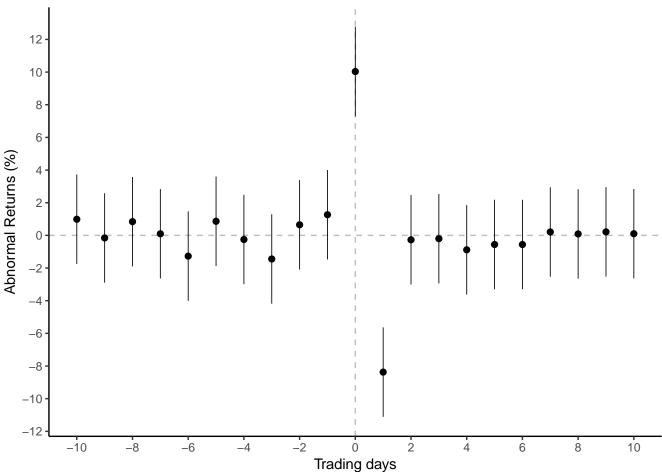


Figure 2: Abnormal returns surrounding the 2002 Venezuelan coup d'etat attempt

The failed coup attempt against Hugo Chavez allows us to examine the effects of both pro-business and anti-business regime change separately from simple uncertainty because investors reacted to an expected regime change twice: first, when Chavez was ousted, and second, when he was reinstated. On the evening of April 11, 2002, coup plotters removed Chavez from office and later detained him. Pedro Carmona, a Venezuelan economist and business leader, was named the transitional President of Venezuela. Two days later, on April 13, 2002, a popular uprising led to Chavez's reinstatement as president. This provides an estimate of the market's valuation of a transition from the Chavez regime to the Carmona regime and its valuation of a transition from the Carmona regime back to the Chavez regime.

By extension, it provides an estimate of the impact of a shift from a left-wing populist government to a pro business regime in an emerging market.

Figure 2 provides graphical evidence on the effect of the coup attempt. The top panel shows CARs for the 10 days prior to and following the event, along with 95% confidence intervals. The daily ARs and corresponding confidence intervals are displayed in the bottom panel. The abnormal return on April 12, the first trading day in which investors could react to the coup, was 10%. The market reacted similarly, albeit in the opposite direction, to Chavez's reinstatement as president: the abnormal return on the next trading day, April 15, 2002, was -8%.

The results in the figure are particularly striking given the discrepancy between the ARs on event days 0 and 1 and all other days. The only days on which the ARs are statistically different from zero is on event days 0 and 1 after the coup attempt.

The almost 0% 10-day CAR preceding the coup makes this an ideal case as it implies that investors were unaware of the coup plot. The unexpected nature of the event means that the abnormal returns capture the true value of the regime change from Chavez to Carmona more accurately than they otherwise would.

3.1.2 Assassinations

The results in Table 4 are produced from analyses identical to those table Table 3 but for successful assassinations rather than coups. Like the majority of coups, there is evidence that assassinations decrease stock prices. The mean event day abnormal return is negative and statistically different than zero. However, the result is driven by five events: the shooting of U.S. President William McKinley on September 6, 1901; the assassination of U.S. President John F. Kennedy on November 22, 1963; the assassination of Indian Prime Minister Indira Gandhi on October 31, 1984; the suicide bombing that killed Sri Lankan president Ranasinghe Premadasa on May 1, 1993; and the assassination of Israeli Prime Minister Yitzhak Rabin on the evening of November 4, 1995.

These results are consistent with our hypothesis that the nature of the political event and

Table 4: Abnormal returns following assassinations

		Post-Event CAR			Pre-Eve	Days to	
Country	Event Date	(0,0)	(0,6)	(0,19)	(-1,-7)	(-1,-20)	rebound
United States	09/07/1901	-4.522	-3.055	-8.920	-0.733	3.456	963
		(1.283)	(3.394)	(5.738)	(3.394)	(5.738)	
United States	11/22/1963	-2.973	2.451	2.267	-2.666	-2.720	2
		(0.470)	(1.242)	(2.100)	(1.242)	(2.100)	
South Korea	10/26/1979	-0.364	-9.376	1.186	0.690	-0.368	14
		(1.058)	(2.800)	(4.734)	(2.800)	(4.734)	
India	11/05/1984	-2.416	-1.259	-2.416	-3.916	1.344	5
		(0.668)	(1.767)	(2.987)	(1.767)	(2.987)	
Sweden	03/03/1986	0.698	5.038	10.908	-3.754	0.955	
		(0.927)	(2.452)	(4.145)	(2.452)	(4.145)	
Sri Lanka	05/03/1993	-3.231	-0.983	3.515	-0.541	-1.360	7
		(0.767)	(2.030)	(3.432)	(2.030)	(3.432)	
Israel	11/05/1995	-3.460	-3.177	0.743	-0.857	-10.316	12
		(1.473)	(3.897)	(6.587)	(3.897)	(6.587)	
Nepal	06/12/2001	-0.513	2.965	15.516	5.956	1.791	20
		(3.513)	(9.295)	(15.711)	(9.295)	(15.711)	
Mean		-2.098	-0.924	2.850	-0.728	-0.902	146
		(0.550)	(1.456)	(2.462)	(1.456)	(2.462)	

Notes: Standard errors are in parentheses. "Days to rebound" is the number of trading days following a negative stock return for the national stock index to return to pre-event level (it is calculated if the price decreases on the event day, not if the event day abnormal return is negative). Returns are inflation adjusted.

its expected impact on policy matters. While the mean effect of assassinations is negative, it is smaller in magnitude than for coups. Unlike a coup, an assassination is typically an unexpected event that may not necessarily cause immediate change in economic policy. As such, we would expect CARs to be negative due to increased instability and uncertainty, but smaller in magnitude to a coup or resignation due to greater expectations of policy inertia.

There is no evidence of post or pre-event CARs in almost any of the assassinations. This is consistent with expectations as assassinations are typically not predictable. As with coups, the number of days that it took the stock market to rebound to pre-event levels is fairly low.¹¹

¹¹One exception is the assassination of William Mckinley in which the stock market didn't fully recover for 963 days, or almost 4 calendar years. However, this was likely caused by the Panic of 1901, which began when the stock market crashed on May 17th, 1901, and not by McKinley's death (although the assassination may have exacerbated the panic). In any case, the length of this time period is so long that we omitted it when calculating the mean days to rebound in the figure.

Table 5: Abnormal returns following resignations

		Post-Event CAR			Pre-Eve	Pre-Event CAR		
Country	Event Date	(0,0)	(0,6)	(0,19)	(-1,-7)	(-1,-20)	Days to rebound	
Argentina	06/18/1982	18.892	24.904	65.863	-2.819	28.234		
	, ,	(3.334)	(8.822)	(14.912)	(8.822)	(14.912)		
Philippines	02/26/1986	$\hat{1}2.938^{'}$	$21.473^{'}$	23.086	$-1.847^{'}$	-6.884		
	, ,	(0.477)	(1.263)	(2.134)	(1.263)	(2.134)		
Bangladesh	12/07/1990	$0.323^{'}$	$1.002^{'}$	$2.171^{'}$	1.880	3.654		
	, ,	(0.871)	(2.305)	(3.896)	(2.305)	(3.896)		
Thailand	05/25/1992	3.248	-6.574	3.789	-5.085	-10.841		
		(1.433)	(3.793)	(6.411)	(3.793)	(6.411)		
Pakistan	04/19/1993	-3.265	-0.432	2.771	-0.312	-0.485	15	
		(1.108)	(2.930)	(4.953)	(2.930)	(4.953)		
Pakistan	11/06/1996	5.084	1.229	-0.441	4.182	7.597		
		(1.416)	(3.746)	(6.331)	(3.746)	(6.331)		
Turkey	06/30/1997	2.010	-2.861	-7.629	12.876	4.532		
		(3.015)	(7.976)	(13.481)	(7.976)	(13.481)		
Indonesia	05/20/1998	2.817	4.296	4.543	-2.695	-17.868		
		(3.392)	(8.974)	(15.168)	(8.974)	(15.168)		
Philippines	01/19/2001	1.150	16.837	18.469	-5.382	3.581		
		(1.591)	(4.209)	(7.115)	(4.209)	(7.115)		
Argentina	12/20/2001	14.015	48.103	62.191	14.656	36.165		
		(1.976)	(5.227)	(8.836)	(5.227)	(8.836)		
Lithuania	04/06/2004	-0.575	-3.319	-11.704	2.182	5.426	159	
		(1.137)	(3.007)	(5.083)	(3.007)	(5.083)		
Ukraine	12/28/2004	5.118	12.837	18.445	4.170	32.085		
		(2.797)	(7.401)	(12.511)	(7.401)	(12.511)		
Ecuador	04/20/2005	-0.084	-0.249	-0.595	-1.305	0.710		
		(0.945)	(2.499)	(4.225)	(2.499)	(4.225)		
Nepal	04/25/2006	1.915	8.132	9.937	-1.951	-4.205		
		(0.665)	(1.760)	(2.975)	(1.760)	(2.975)		
Tunisia	01/31/2011	-2.705	2.982	-11.787	-13.610	-13.445	5	
		(0.671)	(1.776)	(3.002)	(1.776)	(3.002)		
Mean		4.059	8.557	11.941	0.329	4.550	59	
		(0.496)	(1.312)	(2.217)	(1.312)	(2.217)		

Notes: Standard errors are in parentheses. "Days to rebound" is the number of trading days following a negative stock return for the national stock index to return to pre-event level (it is calculated if the price decreases on the event day, not if the event day abnormal return is negative). Returns are inflation adjusted.

3.1.3 Resignations

In contrast to coups and assassinations, abnormal returns following resignations are large and positive (see Table 5). The mean event day abnormal return is over 4% and the positive returns are persistent and grow larger over time (mean 20-day CAR $\approx 11\%$). Furthermore, event day ARs are only negative and statistically significant at even the ten percent level in two out of the fifteen resignations (Pakistan on April 19, 1993 and Tunisia on June 31,

2011).

These results are consistent with the idea that the expected impact of a political event on economic policy is highly important to the directionality of returns. The positive event day abnormal return following resignations is not surprising since resignations typically occur because of poor performance and/or loss of authority. Leaders were often ousted following corruption charges, allegations of fraud, financial crises, and/or political violence.

For example, consider Ferdinand Marcos' resignation from office as President of the Philippines in February 1986. Prior to his resignation, the Philippine regime was known for rampant corruption, crony capitalism, extreme inequality, high unemployment, failed import substitution industrialization policy, and oligarchic control of the economy (Overholt 1986; Traywick 2014). In fact, the Philippines was the least preferred site for foreign investment amongst East Asian capitalist economies and possessed one of the worst capital investment to economic output ratios in Asia (Overholt 1986). Marcos held a snap presidential election on February 7, 1986, in which he declared victory despite overwhelming evidence of electoral fraud. Public protests ensued, and two weeks later the military withdrew its support of the Marcos regime (Lee 2009). Marcos was replaced by his electoral opponent, Corazon Aquino, who had run on a platform of economic liberalization and elimination of crony capitalism (Villegas 1987).

3.1.4 Public Protests

The resignations studied in this paper are those in which leaders left office because of poor performance, public discontent and popular protests. While the previous section showed that the resignations themselves had large effects on stock returns, it is not unreasonable to expect the political actions preceding the resignations to have similarly large effects on financial markets. Indeed, corporate investors in the 2013 MIGA World Investment and Political Risk ranked civil disturbances as the fourth most concerning type of political risk.

A recent example of a popular uprising preceding a resignation is the 2011 Egyptian

Revolution that resulted in the overthrow of President Hosni Mubarak's regime.¹² Clashes between security forces and protestors led to the deaths of hundreds of citizens and injuries to thousands more. The uprising began on January 25, 2011 when millions of protestors demanded the overthrow of the Egyptian leadership. Examples of public discontent included demonstrations, marches, riots, non-violent civil disobedience, and labor strikes.

The short-term impact of the Egyptian Revolution on the economy was disastrous. As shown in Figure 3, abnormal returns on the Egyptian Stock Exchange Index (EGX 30) were around -7% on January 26th and -10% the day after. To prevent further decline during the uprising, the Egyptian Stock Exchanged closed at the end of trading on January 27th. President Mubarak resigned on February 11, but the market remained closed until March 23, when CARs declined by another 9%, before rebounding slightly thereafter.

An important question is whether other popular uprisings have had similar adverse economic consequences. To examine this, we explore all resignations that were driven by significant public protests.¹³ Public protests include popular demonstrations, riots, non-violent civil resistance and other forms of public discontent. These events are listed in Table A.1 in the appendix.

The start and end dates in Table A.1 are the dates that protests began and leader's resigned respectively. Resignations caused by popular uprisings were identified by examining the descriptions in the Coup d'etat Events Handbook and Archigos Version 4.1. Additional Lexis Nexis searches were used to verify these descriptions.

In Table 6, we examine whether public protests influence stock prices. The variable *Protest* is equal to 1 during the dates in which citizens participate in political activities demanding the resignation of the executive and 0 otherwise. Non-protest dates are the 250 days prior to the start dates and after the end dates listed in Table A.1.¹⁴

¹²Abnormal returns for this event are not shown in Table 5 because the stock market was closed on the day of Mubarak's resignation.

¹³The set of resignations includes all those listed in either the Coup d'etat Events Handbook or the Archigos Version 4.1 data set with available financial data. In practice, this is the 2011 Egyptian Revolution and the list or resignations in Table 5.

¹⁴The volatility estimates used as the dependent variable in column (4) are estimated on the 250 days

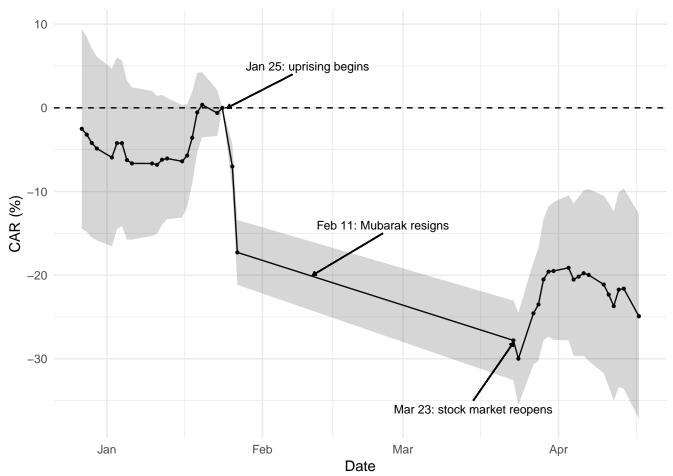


Figure 3: Cumulative abnormal returns during the Egyptian revolution

Column (1) suggests that public protests have no effect on stock returns. However, this occurs because some political movements increase stock prices while others decrease them. As shown in column (2), the absolute value of stock returns are over 2% higher during public protests. These estimates would be biased if protest dates are correlated with higher world or regional stock market indices. To address this potential confounder, column (3) controls for returns on the S&P/IFC Emerging Markets Investable Composite Stock Index. The coefficient on *Protest* barely changes and the absolute value of returns are still about 2% higher during public protests. Finally, column (4) shows that stock volatility is more than 1 percentage point higher during political movements.¹⁵

prior to the start date, the protest dates, and the 250 days following the end date.

¹⁵Volatility estimation methodology is described in detail in Section 3.2.

We therefore find that both volatility and the absolute value of returns increase during times of protest. Similarly to coups, however, the direction of returns is dependent upon the nature of the protest in question.

Table 6: Effect of public protests on stock prices

	Returns	Absolute	Absolute Value of Returns	
	(1)	(2)	(3)	$\overline{\qquad}$ (4)
Protest	0.261	1.485	1.313	0.891
	(0.700)	(0.412)	(0.387)	(0.346)
Emerging market index	, ,	,	$0.075^{'}$, ,
			(0.058)	
Event fixed effect?	Yes	Yes	Yes	Yes
Observations	3,537	3,537	2,676	3,537
Events	11	11	8	11

Notes: Standard errors clustered by event are in parentheses.

3.2 Volatility

Although irregular regime changes have disparate effects on the direction of stock returns depending on expected policy outcomes, the results from Section 3.1 suggest that all of these political events increase financial volatility. However, since stock volatility is not directly observable, one must decide how to best estimate volatility. Our estimates are obtained from a generalized autoregressive conditional heteroskedasticity (GARCH) model estimated using 1000 pre-event days, the event day and 1000 post-event days. As in Jensen and Schmith (2005) and Leblang and Mukherjee (2005), we use the GARCH (1,1) specification. In particular, for national stock index i,

$$R_{it} = \mu_i + \epsilon_{it}, \qquad \epsilon_{it} \sim \mathcal{N}\left(0, \sigma_{it}^2\right),$$

where μ_i is a constant and,

$$\sigma_{it}^2 = \gamma_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2.$$

The key parameter of interest is the conditional variance, σ_{it}^2 . The one-period-ahead volatility forecasts, σ_{it} , are larger when $\epsilon_{i,t-1}^2$ and $\sigma_{i,t-1}^2$ are larger. In other words, the model predicts that large shocks will be followed by other large shocks.

Figure 4 shows the mean volatility ($\overline{\sigma_t}$) estimates from the GARCH (1,1) model across all irregular regime changes for 30 trading days prior to and 30 days after each event. Volatility appears to increase slowly just before the regime change, which suggests that investors sometimes have information about the events before they occur. Nonetheless, there is still an enormous volatility jump on the day of the regime change. Volatility then decreases to normal levels within a month of the event.

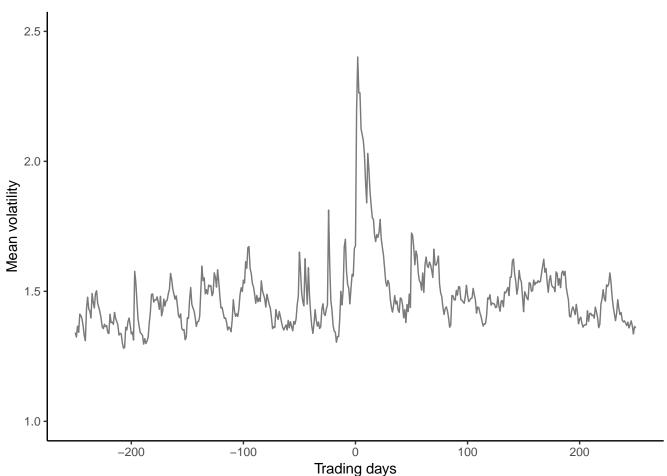


Figure 4: Mean of volatility estimates from GARCH(1,1) models

The smaller figure within Figure 4 expands the volatility estimates to the 250 trading

days before and after each regime change. As expected, the volatility estimates stay between a narrow range at nearly all dates except those surrounding the regime change.

3.3 Robustness

There are three potential concerns with the results in Section 3.1. First, the abnormal returns could have been driven by factors unrelated to the regime changes. Second, the reported means are based on small sample sizes so confidence intervals based on normally distributed abnormal returns may be inappropriate. Third, the true effects of irregular regime changes on firm value may be underestimated if investors had apriori information.

To explore the first concern, we create a synthetic control portfolio for each event based on the techniques introduced in Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010). Each country is given a weight which represents its influence in the synthetic control portfolio. The weight is chosen so that the daily returns and the variance of the daily returns of the control portfolio and the event country are most similar in the estimation window. The set of possible countries in the control portfolio consists of all countries listed in Table 2.¹⁶

The second concern is addressed using non-parametric statistical techniques, which are free from distributional assumptions. We employ the sign and the rank tests which are based on the sign and the rank of the event day ARs respectively.¹⁷ Both tests are less influenced by departures from normality than statistics based on traditional t-tests such as those reported earlier in this paper.

Table 7 compares event day ARs as well as "abnormal absolute returns" between the event country and the synthetic control portfolio using the non-parametric methods discussed above. The "abnormal absolute returns" are abnormal returns for the absolute value of stock returns. This is done to combine events since resignations tend to increase returns while assassinations and coups tend to decrease them. The idea that the absolute value of

¹⁶See the appendix for a more formal explanation.

¹⁷See section 8 in MacKinlay (1997) for more details.

returns might increase during irregular regime changes is similar to the finding that volatility increases and is consistent with Figure 1.

Table 7: Non-parametric tests of the impact of regime changes

	Regime Change Country			Synthetic	Wilcoxon		
	Mean	Rank	Sign	Mean	Rank	Sign	Rank Test
Event Type	CAR(0,0)	p-value	p-value	CAR(0,0)	p-value	p-value	p-Value
Coups	-2.137	0.006	0.022	0.024	0.702	1.000	0.002
Assassinations	-2.098	0.001	0.070	-0.125	0.255	0.453	0.078
Resignations	4.059	0.010	0.118	0.366	0.778	0.607	0.048
All (Absolute Value)	2.410	0.002	0.033	-0.079	0.879	0.955	0.000

Notes: Estimates for assassinations do not include the assassination of U.S. president William McKinley in 1901 because no control portfolios are available. Two-sided

As shown in Table 7, the mean event day abnormal returns for coups, assassinations and resignations are all statistically different from zero at the 1% level using the rank test statistic and the abnormal returns for coups and assassinations are significant at at least the 10% level using the sign test. In addition, abnormal absolute returns for all events are statistically significant at the 5% level using both the rank and sign statistics. On the other hand, the event day abnormal returns for the control portfolio are never statistically different from zero at even the 10% level. Finally, the difference in means between the regime change country and the control portfolio are statistically different from zero for coups (1% level), assassinations (10% level), resignations (5% level), and all events combined (1% level) when using two-sided p-values from the Wilcoxon rank test. In sum, these results suggests that the results from section Section 3.1 are not an artifact of deviations from normality or confounding world events.

The third concern, which is that the political events in this paper are not unexpected, is addressed in a number of ways. First, one can note that although some of the irregular regime changes have statistically significant pre-event CAR's, most of them do not, and the ones that do not always move in the same direction. For example, there was a positive

¹⁸The Wilcoxon rank test is a non-parametric statistical technique that can be used to compare differences between matched samples.

14.7% 7-day CAR preceding the resignation of President Fernando de la Rua of Argentina in December of 2001, even though the resignation was associated with large positive event day abnormal returns.

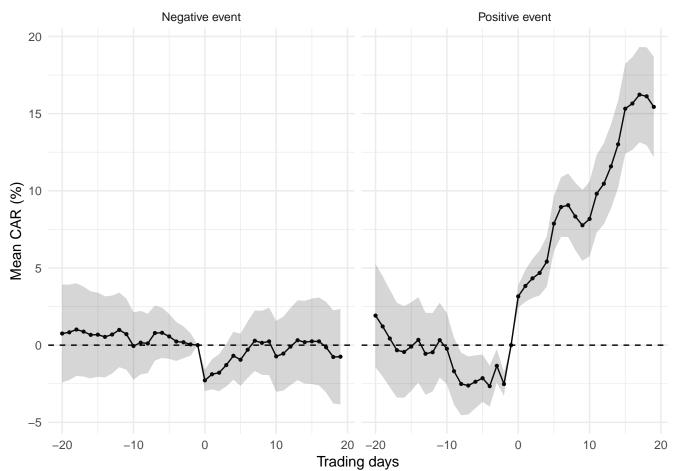


Figure 5: Mean cumulative abnormal returns surrounding regime changes

Second, since the direction of the pre-trends is unclear, we examine whether there are different pre-trends for events with positive stock reactions than for events with negative stock reactions. As shown in Figure 5, neither the "positive" nor "negative" events have pre-event CAR's that are statistically different from 0. Furthermore, for negative events, almost all of the stock-market reaction occurs on the first day that the market could react to the event which implies that markets are responding quickly to negative political events. On the other hand, the effect of positive event seems to be longer lasting with CARs increasing

during the 20-day post-event window.

4 Conclusion

This paper has examined the effects of irregular regime changes on financial returns. It uses an event study approach to show that investors expect irregular regime changes to have large effects on equity returns. This methodology is less susceptible to endogeneity biases than studies that use cross country data.

The results are consistent with the idea that perceptions of government competence and changes in government have large impacts on investor confidence. Financial volatility surrounding regime changes, which is often characterized by large negative and positive stock returns, suggests that irregular regime changes increase policy uncertainty and volatility, but that uncertainty does not tell the whole story. The direction of returns depends on the expected outcome of the irregular regime change. The variation in the direction of abnormal returns is therefore consistent with the idea that not all types of regime changes are equivalent in terms of expected economic policy outcomes. Abnormal returns are likely positive following resignations because those leaders were likely to be "bad" leaders, and coups may result in positive returns in the event of a transition to more democratic or pro-business leadership.

A Appendix

Table A.1: List of public protests preceding resignations

Country	Name	Start Date	End Date
Philippines	EDSA 1/Yellow Revolution	2/22/1986	2/25/1986
Bangladesh	Bangladeshi Spring of 1990	11/27/1990	12/7/1990
Thailand	Black May	5/17/1992	5/20/1992
Indonesia	Indonesian Riots	5/12/1998	5/21/1998
Philippines	EDSA II	1/17/2001	1/20/2001
Argentina	Argentina Riots	12/16/2001	12/20/2001
Ukraine	Orange Revolution	11/22/2004	1/23/2005
Ecuador	Ecuadorian Protests	4/13/2005	4/20/2005
Nepal	Nepalese People's Revolution	4/6/2006	4/24/2006
Tunisia	Tunisian Revolution	12/18/2010	1/14/2011
Egypt	Egyptian Revolution	1/25/2011	2/11/2001

A.1 Synthetic Control Portfolio

Let \mathbf{R}_k be the vector of returns for the event country in the estimation window, \mathbf{R}_{-k} be the vector of returns for all other countries in the estimation window, $\mathbf{X}_1 = (\mathbf{R}_k, \operatorname{Var}(\mathbf{R}_k))$, $\mathbf{X}_0 = (\mathbf{R}_{-k}, \operatorname{Var}(\mathbf{R}_{-k}))$, and \mathbf{W}_{-k} be a $((N-1)\times 1)$ vector of weights where N is the number of countries listed in Table 2. Then \mathbf{W}^* is chosen to minimize $(\mathbf{X}_1 - \mathbf{X}_0 \mathbf{W})' \mathbf{V} (\mathbf{X}_1 - \mathbf{X}_0 \mathbf{W})$ subject to $w_i \geq 0$ (i = 1, 2, ..., N-1) and $\sum_i^{N-1} w_i = 1$, and the vector \mathbf{V} is chosen so that stock returns for the control portfolio during the estimation window are are close as possible to the event country.¹⁹

 $^{^{19}}$ See Abadie and Gardeazabal (2003) for further details.

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