# Leaders and Markets: National Leadership and Stock Market Performance

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**Abstract**

We use random exits of heads of state to determine whether these exogenous transitions are associated to changes in stock market returns across countries. We focus on the cases in which the leader's rule ended due to either a sudden accident or after a long-standing illness. We find that an accident does not trigger a significant change in abnormal returns or volatility. An exit after illness, however, is associated to a positive and significant change in abnormal returns, but no change in volatility. Using data on rumors about leaders' health, we find that the start of a string of rumors is associated to a significant drop in abnormal returns, but no change in volatility. This suggests that news about a leader's ailment generates expectations of deficient rule. Further analysis suggests that the significant drop-and-rebound effect is strongest in autocratic countries and in regimes where the leader has low levels of education.

**Keywords:** political leaders; stock market returns; political regime.

**JEL Classification:** D53; G14; G15.

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# 1 Introduction

Heads of state influence policies, laws, regulations, and enforcing agencies that shape market expectations. The influence of a leader, however, reaches beyond formal institutions and largely depends on the scope of his personal power. Although there has been an increasing interest to study the role of national leaders on economic outcomes (e.g., Jones and Olken, 2005), little is still known about the influence of national leaders on markets across countries. We believe this is particularly important because the personal power of a leader must be constrained to secure property rights to foster markets (North, 1990; Williamson, 1985) and because institutions that constrain a leader's personal power operate only partially and recently in a few advanced countries (Greif and Kandel, 1995; Greif, 2008).

We study the effect of leaders on stock markets. We assess the performance of equity markets around leader transitions that are unrelated to the underlying economic conditions. We focus on stock markets because they represent a large portion of the assets traded in an economy, because they reflect expectations about the future performance of the economy, and because comparable cross-country data can be collected. We focus on leader transitions in which the leader's rule ended due to either the worsening of a long illness or a sudden accident. We do this because the timing of transition is essentially random. These exit events, coupled with stock price data, provide an opportunity to study whether an exogenous change in the identity of the head of state has a significant effect on markets.

Markets should respond differently to a leader's exit due to an accident and a long-standing illness. Accidents are surprising as markets do not anticipate them. Exits triggered by illnesses, on the other hand, are likely to be preceded by market adjustments following rumors about a leader's ailment. Considering these two cases is important not only because rumors contain information about a leader's fitness to perform the activities that high office demands, but also because most of the heads of state reach high office in their late middle age or even old age, when there is a high risk that mental illnesses or physical disabilities manifest (see, e.g., Fisman (2001) for the case of Suharto in Indonesia).[1]

We use a data set collected by the authors on all national leaders who left office randomly between 1923 and 2015 for whom local and global equity indexes were available. We focus on leaders who left office unexpectedly. Our sample is separated into those leaders who exit power after a long-standing illness (most of them died) and those who died in an accident while still in power. We label the former as an *unsurprising* exit and the latter as a *surprising* exit. This sample contains 38 leaders from 28 different countries. Out of the 38 leaders, 23 left office after a long-standing illness and 15 left office as a result of a sudden accident. For each leader, we obtained data on local and global equity indexes from Datastream and Global Financial Data (GFD). In total, we use 10,147 days of stock index data to study unexpected exits. We also consider a placebo group comprising of 157 additional leaders from 20 different countries (a subset of the 28 countries considered for unexpected exits) whose spell ended regularly (completion of their term). For this sample, we use 31,215 days of stock index data.

We find that unsurprising exits lead to a cumulative average abnormal return (CAAR) of at least 1.3%. This CAAR is economically and statistically significant. Surprising exits, on the other hand, are not associated to a significant cumulative average abnormal return. In addition, cumulative abnormal returns (CARs) around surprising exits do not show unusually high or low values given the returns witnessed in that country at other dates. We also find that in none of the two main subsamples, surprising and unsurprising, the exit event is systematically associated to a significant change in volatility. According to the criteria used in Bloom (2009, p. 630), for example, only 2 of the 23 unsurprising exits could be labeled as *volatility shocks*. Similarly, none of the 15 surprising exits could be deemed as a

[1]For example, the life expectancy of two-thirds of American presidents was 2 years shorter than that of the general population (DeMaria, 2003). Evidence from interviews to doctors and from the official record suggests that leaders' ailments may be associated to poor political decision making (see, e.g., Owen, 2003; Post and Park, 1989; Post, 1995). One example is the concessions Franklin D. Roosevelt arguably made to Joseph Stalin at the Yalta conference in 1945.

*volatility shock*. In the placebo group, none of these measures (CAAR, dispersion of CAR, and volatility) are significantly different from zero.

We also examine whether leaders matter more or less depending on whether the country is a democracy or an autocracy. Overall, we find evidence that the exit of an autocratic leader is associated to an increase in abnormal returns. The positive relationship is driven by those autocrats who exit unsurprisingly after a long-standing illness. The exit of a democratic leader is not associated to abnormal returns. In addition, we explore whether there is a relationship between leader's education and returns. We find that the exit of a relatively uneducated leader has a positive effect on abnormal returns; and this result is driven by uneducated leaders who leave office after illness. The exit of educated leaders is not systematically associated to positive or negative abnormal returns. It is important to point out that these results come from further splits of the sample, so although consistent with the previous literature (Jones and Olken, 2005; Besley et al., 2011), may be biased due to small sample size.

We then examine rumors concerning each leader's health during the final period in office. This exercise is particularly relevant, not only because health issues are likely pervasive among heads of state, but because the level effect of exits on cumulative returns is driven by those leaders with health problems. We are able to gather information about rumors for 14 out of the 23 leaders in this subsample. When a string of rumors starts, we find that abnormal returns go down significantly, about 5% on average. We do not see, however, an unusual increase in returns volatility around the date of the rumor: Only 2 out of 14 rumor events can be labeled as *volatility shocks* according to Bloom (2009). These results are consistent with investors considering a leader's impairment as a negative indicator of the future quality of his rule.

The remainder of the paper is organized as follows. Section 2 discusses the existing literature on the role of national leaders and markets. Section 3 presents the methodology and section 4 the data. Section 5 presents the results and section 6 the robustness checks.

Section 7 concludes.

# 2 Leaders and Markets

Economics has been, to a large extent, a field concerned with economic interactions among impersonal agents. Recently, however, increasing attention has been granted to the question of whether the personal characteristics of leaders shape economic outcomes. Jones and Olken (2005), for example, show that leaders do matter for economic growth, especially when the institutions are weak. This finding supports theoretical predictions in that leaders should shape economic variables as they influence policies and come to power as a result of political competition (arguably among citizens in democracies or among elite members in autocracies)—so selection is based on ideology, virtue, or talent (see e.g., Osborne and Slivinski, 1996; Besley and Coate, 1997; Caselli and Morelli, 2004; Acemoglu et al., 2010).[2]

Heads of state shape stock market expectations because they influence policies, laws, and regulations, which in turn affect the institutions that support markets. According to the Hobbesian view, a strong government is needed to protect property rights and ultimately foster markets. A strong government, however, might also expand the leader's coercive power. A common perception that a leader's power enables him or her to abuse others' rights, which may discourage individuals from participating in the market in the first place (Greif, 2008). The extent to which a leader can use his influence to further his self-interest by modifying market-supporting institutions (such as auditing or supervisory requirements to

[2]Partisan identity seems to matter as well. In the U.S., for example, Santa-Clara and Valkanov (2003) find that the excess returns in the stock markets are higher under Democratic than under Republican presidencies. Snowberg et al. (2007), using exogenous changes in expectations as to who will be the winner during the 2004 presidential election, find that markets anticipated higher equity prices under a George W. Bush presidency than under John Kerry. There are more examples. In fact, there is a large literature documenting the difference in stock returns under Republican and Democratic presidents in the United States (see e.g., Herbst and Slinkman, 1984; Alesina et al., 1997; Siegel and Coxe, 2002; Johnson et al., 1999; Drazen, 2001). In the U.K., Herron (2000) reports a positive correlation between the odds of Labour Party victory and changes in British stock indexes.

economic transactions or judicially punishing violators of contracts) depends on his personal ethics and capacity to administer a government. Governments, however, rarely provide impartial contract enforcement institutions (Williamson, 1985; Greif and Kandel, 1995). Markets therefore should react to the unexpected exit of a powerful ruler. In fact, evidence is consistent with this idea. Knight (2006), for example, found that in the Bush-Gore 2000 election in the U.S. Bush-favored firms were worth 16% more than Gore-favored firms under the subsequent Bush administration. More broadly, using a sample of 47 countries, Faccio (2006) documents a significant increase in the value of equity of a firm when a businessperson involved in that firm is elected as a prime minister. Fisman (2001) uses data on rumors about Suharto's (Indonesia's former president) health between 1995 and 1997 to estimate the effect of such news on firms' stock returns with different degrees of connectedness to Suharto. He also finds that firms connected to Suharto lost significantly more market value than did less-dependent firms. At the time, Indonesia was considered among the most corrupt countries in the world in the "Perceived Corruption Ranking 1998." Nevertheless, the market overall declined whenever it received adverse information regarding Suharto's health.

Apart from the institutional arrangement, evidence suggests that a leader's individual characteristics also matter. An important feature is the fitness to perform the complex tasks that high office demands. Political leaders tend to achieve high office in late middle age or even old age. Although most studies of political leadership assume leaders are in full mental and physical capacity, they are likely to be afflicted by mental or physical impairment (Post, 1995; Park, 1986). The decisions of ailing leaders therefore may not reflect a fair assessment of reality, but rather emotions, illusions, or the biased advice from members of his inner circle (Reches, 2006). Evidence from the medical literature suggests that ill leaders tend to lead secretive lives, become out of touch with the people they represent and the world around them, and develop paranoiac tendencies (Owen, 2003). Leaders are likely to hide their ailments and exert power through imposition rather than popular consent. In addition, leaders' health issues may increase uncertainty as to who is actually running the government.

In the face of political uncertainty, empirical evidence suggests that economic agents refrain from investing, which ultimately undermines future economic performance (see, e.g., Barro, 1991; Alesina and Perotti, 1996; Pindyck and Solimano, 1993; Mauro, 1995; Julio and Yook, 2012; Gulen and Ion, 2015; Bloom, 2009).[3]

Our paper contributes to a growing literature on whether national leaders matter for broad-based economic variables. It provides a causal analysis as to whether heads of state matter for stock returns using a cross-country sample that covers almost 100 years. Examining the effect of leaders on markets can therefore provide a useful test for whether coercion-constraining institutions actually work at large. In addition, we study whether leader specific effects are contingent upon settings in which they are relatively unconstrained (autocratic regimens) and have relatively low levels of education. We also examine whether the health of the national leader, a common yet largely overlooked characteristic, affects stock market outcomes. Finally, we find that the overall decline in the market, following adverse news about the leader's health, is partially recovered when the impaired leader leaves office.

# 3 Methodology

The main question in this paper is whether equity indexes' abnormal returns significantly change across leaders' exits. To answer this question, we compute the abnormal returns associated to each exit, and assess whether the average and dispersion of these returns across exits are significantly different from zero.

[3]The argument is that for investment projects that are not fully reversible, uncertainty increases the option value of waiting until some of or all the uncertainty is resolved (Bernanke, 1983; Rodrik, 1991; Pindyck and Solimano, 1993; Bloom et al., 2007).

### 3.1 Average Abnormal Returns

We compute abnormal returns (AR) for each day around a leader's exit in our sample. The abnormal return is the difference between the return of the country index and a benchmark return based on the world index. Following Patell (1976), and using the market model introduced by Sharpe (1964) and Lintner (1965), the AR around leader exit $j$ at time $t$ is:

$$AR_{j,t} = R_{j,t} - \left(\hat{\alpha}^*_j + \hat{\beta}^*_j \cdot R_{w,j,t}\right), \tag{1}$$

where $R_{j,t}$ is the return of the country index associated to leader exit $j$ in day $t$ and $R_{w,j,t}$ is the return of the world index in day $t$.[4] Thus, $(\hat{\alpha}^*_j + \hat{\beta}^*_j \cdot R_{w,j,t})$ is the benchmark return in day $t$ associated to leader exit $j$.[5] We estimate the parameters of the model, $\hat{\alpha}^*_j$ and $\hat{\beta}^*_j$, using the method proposed by Scholes and Williams (1977) to account for non-synchronous trading.[6] See Appendix 8.2 for a detailed explanation on these estimators.

The cumulative average abnormal return (CAAR) is the cross-sectional average of cumulative abnormal returns (CARs) in the event window. Formally, the CAAR between trading day $T_1$ and trading day $T_2$ is computed as follows:

$$CAAR_{T_1,T_2} = \frac{1}{N}\sum_{j=1}^{N} CAR^j_{T_1,T_2} = \frac{1}{N}\sum_{j=1}^{N}\sum_{t=T_1}^{T_2} AR_{j,t}.$$

where $N$ is the number of events.

[4]Note that we use the convention to label $t$ to indicate the time period to and from the event, which occurs at $t = 0$.

[5]Despite its simplicity, the market model provides a good benchmark for well-diversified indexes such as the ones used in this paper. Multifactor models such as Fama and French (1993)'s are unfeasible in our context, since Fama-French factors are not available for the global market.

[6]Most financial models assume that trading price data is available at regular, fixed-time intervals. However, the time at which trading occurs does not follow a regular process but rather takes place discretely and stochastically. The discontinuity in trading is known as non-synchronous trading and should be accounted for while estimating the parameters of the models.

Appendix 8.3 presents the $Z$ statistic for the null hypothesis that the CAAR is equal to zero. Under regular assumptions, this $Z$ statistic follows a Standard Normal distribution. Reported significance levels are computed using this $Z$ statistic. A complementary analysis using bootstrapping is presented in Appendix 8.4. Bootstrapped p-values based on the empirical distribution of the CAAR are also reported as part of our results.

### 3.2 Dispersion of Returns

Even if the CAAR is not significantly different from zero, it is plausible that extreme negative and positive CARs around the leaders' exits average out to zero. We consider a general non-parametric test to determine whether the CARs around leaders' exits are unusually extreme when compared to the CARs observed in those countries in other periods that do not include the event. In particular, we adapt the non-parametric rank test used in Jones and Olken (2005) to assess whether the CARs take on extreme values compared to their corresponding time-series means.

As a first step, for each leader $j$, we compute the percentile rank of the CAR around the date of exit with respect to auxiliary CARs for neighboring windows. Due to data availability we consider windows over the period ranging from -190 days before and 60 days after the leader left office.[7] Under the null hypothesis the percentile rank of the relevant CAR, $rank_j$, is uniformly distributed over the interval $[0, 1]$. In order to test the null hypothesis, we define $y_j = |rank_j - 1/2|$ and use the following test-statistic:

$$K = \frac{\sum_{j=1}^{N} (y_j - \frac{1}{4})}{\sqrt{N/48}}. \tag{2}$$

[7]Due to the same reason, when studying the effect of rumors, we consider a window with the same length but from day -106 to day 144 after the rumor was published. Similarly, we consider a window from day -167 to day 83 to study the placebo group.

Under the null $K$ should have zero mean.[8] Therefore, we perform a one-sided non-parametric test of whether $K$ is systematically larger than zero. The details on this test are presented in Appendix 8.5.

### 3.3 Volatility of Returns

To test whether the exit events are systematically associated to significant changes in volatility, we follow Bloom (2009) and see if each exit in our sample can be deemed as a *volatility shock* or not. For each exit, we compute 49 monthly volatilities; one for the calendar month of the exit, and one for each of the 24 months before and after. Each monthly volatility is computed as the standard deviation of daily stock return within the relevant calendar month. Then, we standardized the monthly volatility around the exit by subtracting the mean and dividing by the standard deviation of the 49 volatilities associated to that leader. We identify a *volatility shock* by comparing this standardized volatility 1.65, the 5% one-tailed critical value of the Normal distribution.

As an alternative, we also study changes in both volatility and betas, by comparing average values before and after the exit events. For each exit, we define two non-overlapping windows of equal length, one immediately before (i.e., $[-n, -1]$) and one immediately after (i.e., $[1, n]$) the day that the event takes place (day 0). Within these windows, we compute volatilities as standard deviations of daily stock returns, and betas using the method proposed by Scholes and Williams (1977) to account for non-synchronous trading. Finally, using a $t$-statistic we test whether the cross-average volatility or beta before the exit is significantly different than the one after.

[8]Since under the null, $E(y_j) = 1/4$ and $Var(y_j) = 1/48$.

# 4 Data

## 4.1 Leaders

We are interested in identifying cases in which the head of state exits power surprisingly (due to an accident) and unsurprisingly (due to long-standing ailment). We build our sample from Archigos (Goemans et al., 2009). This dataset contains information about leaders from 189 countries who took office within 1875 and 2015. Archigos includes information on the country of each leader, the beginning and end of the leader's spell, and the manner in which a leader reached and lost power.

We are interested in national leaders who left power in an irregular manner (e.g. retired due to ill health, died as a result of an accident or natural cause). To identify these leaders, we start by removing all the entries in Archigos for which the variable *Exit* takes the value "Regular". This reduces the number of entries from the original 3,329 to 1,117. We then exclude the entries for which the variable *Exit* takes the value "Foreign" to eliminate any leader deposed by another state. After doing so, our sample comprises 1,045 exits. In addition, we exclude entries with values of *Exit*: "Still in Office" (173 leaders), "Suicide" (3 leaders) and those for which there is no information available (3 leaders). The remaining sample contains 866 leaders that do not overlap with our placebo group.

Some of these 866 exits, however, may still be triggered by underlying economic conditions. To refine our sample, we use the variable *Exitcode*, which provides more specific information about a leader's exit. We remove any exit prompted by a third party as it is deemed as predictable. This includes leaders removed by popular protests (39 leaders), rebel forces (53), military actors (281), and other similar agents (99). The final sample consists of 394 leaders.[9]

[9] As a validation procedure, we compare our sample with the one used by Besley et al. (2011). They use a total of 183 political leaders who were in office between 1875 and 2004. From this list, 174 leaders are also included in our sample. For details, see Appendix 8.1.

## 4.2 National Stock Market Indexes

The 394 leaders who left office in an irregular manner belong to 123 different countries. We need stock market data for each of these countries. We only consider stock market indexes' returns since detailed information on other metrics such as variation in trading volume or intra-day variation on prices (e.g., high-low or bid-ask) are not available for the broad set of leaders in our sample. We retrieve stock market data from Datastream and Global Financial Data (GFD).

While searching in Datastream we focus on series tagged as "Equity Indices" for each country. Most series in Datastream are available only in local currency. Since to compute CAARs we need all series in the same currency, in these cases we also need local exchange rates to convert prices to US dollars. While searching in GFD we focus on series classified as "Stock Indices - Composites" under "Equity" for each country, using both GFDatabase and Eurostat. GDF provides series in US dollars or local currency, we use the former option.

Although we limit our search results to equity indexes, there is still a large number of series remaining to choose from. Most of them are country specific indexes provided by different sources and covering different time periods and subsets of companies. We employ four criteria to select the most relevant series. First, we prefer the longest series available for each country. Second, we prioritize the series with high relative relevance within each database (both Datastream and GFD sort their search results according to relevance). Third, we discard industry-specific indexes because they are not available for all countries. Fourth, we prefer series without gaps and, if needed, we download multiple series in order to cover the longest possible period of time.

Following this procedure, we obtain 139 series from Datastream and 163 series from GFD representing 71 and 83 different countries respectively. For 39 of the 123 countries in our sample of leaders whose spell ended unexpectedly, we did not find any series that met the aforementioned criteria. In contrast, for some countries we gather up to 5 different time series.

## 4.3 World Stock Market Index

As previously mentioned, we compute abnormal returns using a benchmark that depends directly on the world stock market index. To obtain this index, we search for suitable series in Datastream and GFD following the same procedure described in section 4.2, but specifying the as location "World." There are two series with daily information that provide data from 1970 onward: MSWRLD$ from Datastream and _MIWO00D from GFD. The correlation between the returns of these two indexes is 99.8%. We choose the one from Datastream as our main world stock exchange index as it spans a longer period of time in comparison to the one from GFD.

For exits before 1970, we construct a world index using country-specific indexes. Specifically, we compute a weighted average of daily country-specific-index returns using GDP as weight. We re-balance the portfolio annually. GDP data is obtained from the Maddison Project Database (Bolt and van Zanden, 2014). The resulting index contains stock market data from 40 countries that represent, on average, 81% of the world's GDP. As a robustness check, we compute daily returns of our index for the period after 1970 and correlate them with the ones obtained from the world index downloaded from Datastream. The correlation coefficient obtained is 77%.

## 4.4 Final Sample

The final step consists in coupling each one of the 394 leader exits in our sample with one country-specific stock market index. We inspect each series to confirm it contains daily data that includes the date of exit of one of the 394 leaders considered. Leaders that cannot be paired are discarded. We were able to find daily closing price data for 42 leader exits.

As a further validation check, we search elsewhere for specific information about each leader's unexpected exit. For our purposes, we find that Archigos misclassified 4 of these 42 leaders. Both Ghandi, I. (India) and Premadasa (Sri Lanka) should be removed as they were assassinated. Fahd (Saudi Arabia) and Yen Chia-Kan (Taiwan) are also removed as their exit should be classified as regular. Fahd ceded power voluntarily and Yen Chia-Kan ended his term as supposed.

Therefore, our final sample consists of the 38 unexpected exits displayed in Table 1. It is crucial to our analysis whether the leader's exit was preceded by a long-standing illness or not. We combine the information in the column "Reason of Exit" of Table 1 with the information available in Archigos to split the leaders into two subsets. The first subset (referred to as *surprising* henceforth) contains 15 leaders who lost power in a surprising manner. They are leaders for which the Archigos' variable *Exit* takes the value "Natural Death" and died due to either a heart attack, stroke, plane crash, or drowning. The second subset (referred to as *unsurprising* henceforth) is the complement of the one just described and encompasses leaders who left power due to aggravation of a medical condition.

Finally, we use the data available in Archigos to build a placebo group. It contains leaders who stepped down from their position in a regular manner (e.g. completion of their term) for the same countries of the 38 leaders who left office unexpectedly. The resulting set contains 157 additional leaders.

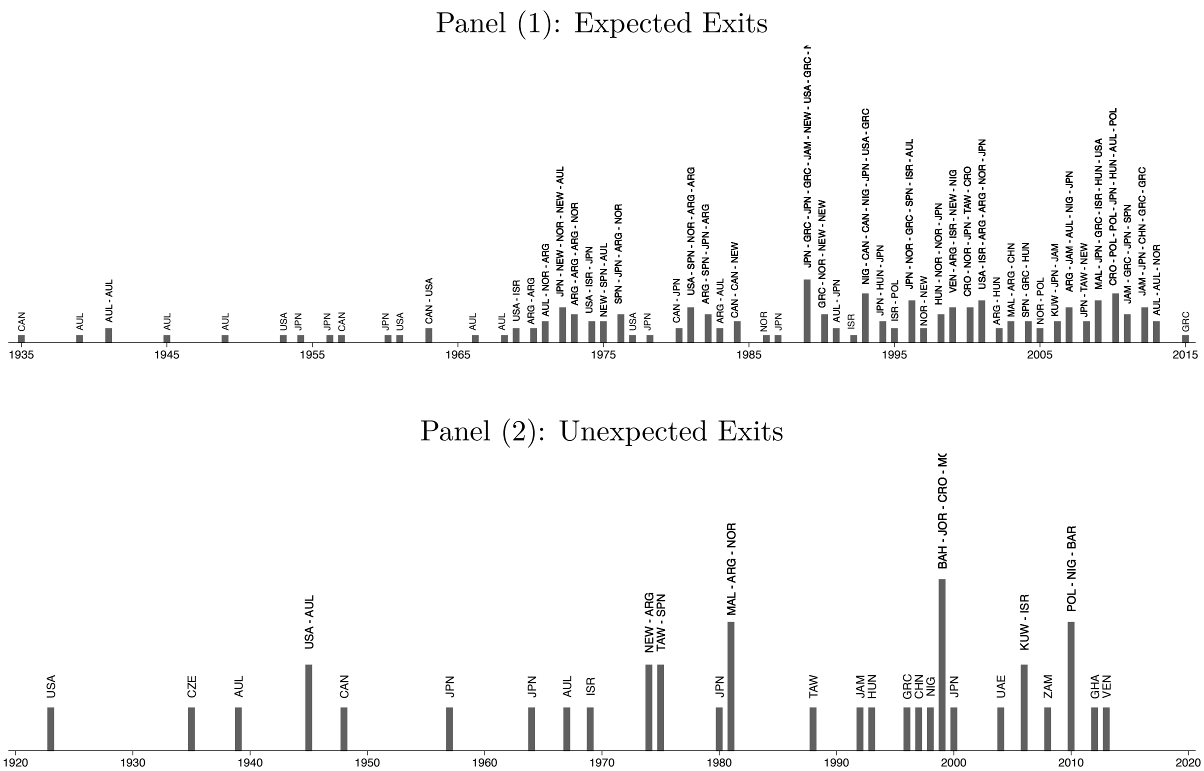



Figure 1: Temporal distribution of the leaders with expected and unexpected exits. Panel (1) shows the timeline of the leaders with regular exits, i.e., those who left power in a regular manner. The column's height indicates the number of leaders per year and it ranges from 0 to 9. There is total of 157 leaders spread out across 20 countries. Panel (2) shows an annual timeline of the leaders with unexpected exits. The column's height indicates the number of leaders per year and it ranges from 0 to 4. There is total of 38 leaders spread out across 28 countries.

Figure 1 and Figure 2 present the time span and geographic coverage of the leaders in our main samples. Panel (1) in Figure 1 shows the temporal distribution of the entries in our placebo group from 1935 until 2015. Panel (2) in Figure 1 shows that our sample of unsurprising exits spans the period of 1920 to 2013. It also shows that although most of the exits that could be matched to stock market data occur after 1970, 10 out of 38 occur before 1970. Figure 2 shows that our sample of unexpected exits contains leaders in countries at different stages of development and spreads out across six different continents.

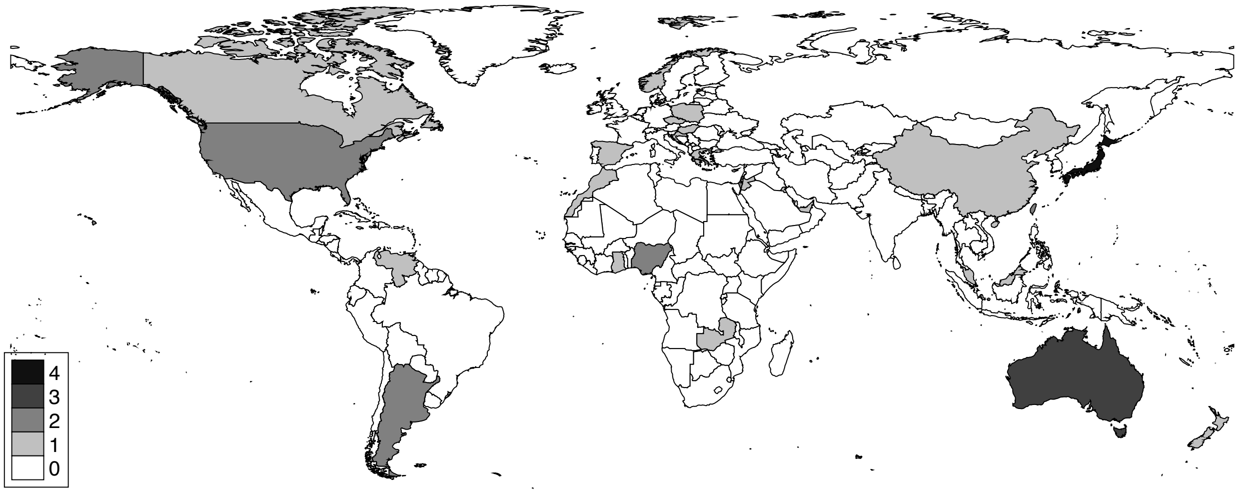



Figure 2: Geographical distribution of the leaders with unexpected exits. The greyscale indicates the number of leaders per country and it ranges from 0 (white) to 4 (black). There is total of 38 leaders spread out across 28 countries.

Table 1: Final Sample

| ID | Name | Country | Series' Ticker | Source | World Series | Reason of Exit | Unsurprising Exit | Date |
|---|---|---|---|---|---|---|---|---|
| GRC-1993 | Andreas Papandreou | Greece | _ATGD | GFD | MSWRLD$ | Heart Failure | Yes | 1/16/1996 |
| ISR-2001 | Ariel Sharon | Israel | _TA100D | GFD | MSWRLD$ | Stroke | Yes | 4/14/2006 |
| TAW-1978 | Chiang Ching-Kuo | Taiwan | _TWIID | GFD | MSWRLD$ | Heart Attack | No | 1/13/1988 |
| TAW-1950 | Chiang Kai-Shek | Taiwan | _TWIID | GFD | MSWRLD$ | Kidney Failure | Yes | 4/5/1975 |
| BAR-2008 | David Thompson | Barbados | BBLOCD | GFD | MSWRLD$ | Cancer: Pancreatic | Yes | 10/23/2010 |
| CHN-1980 | Deng Xiaoping | China | _SSECD | GFD | MSWRLD$ | Parkinson Desease | Yes | 2/19/1997 |
| SPN-1939-2 | Francisco Franco Bahamonde | Spain | _SMSID | GFD | MSWRLD$ | Parkinson Desease | Yes | 10/30/1975 |
| CRO-1990 | Franjo Tudjman | Croatia | _CRBEXD | GFD | MSWRLD$ | Cancer: Stomach | Yes | 11/26/1999 |
| USA-1933 | Franklin D. Roosevelt | United States | _SPXD | GFD | Own | Cerebral Hemorrhage | Yes | 4/12/1945 |
| AUL-1966 | Harold E. Holt | Australia | _AORDD | GFD | Own | Drowning | No | 12/19/1967 |
| MOR-1961 | Hassan II | Morocco | _CFG25D | GFD | MSWRLD$ | Heart Attack | No | 7/23/1999 |
| JPN-1960 | Hayato Ikeda | Japan | _TOPXD | GFD | Own | Pneumonia (Following Treatment Cancer: Laryngeal) | Yes | 10/25/1964 |
| VEN-1999 | Hugo Rafael Chávez Frías | Venezuela | _IBCD | GFD | MSWRLD$ | Heart Attack | No | 3/5/2013 |
| JOR-1952 | Hussein Bin Talal El-Hashim | Jordan | _AMMAND | GFD | MSWRLD$ | Cancer: Non-Hodgkin's Lymphoma | Yes | 2/7/1999 |
| MAL-1976 | Hussein Bin Onn | Malaysia | _KLSED | GFD | MSWRLD$ | Heart Attack | Yes | 7/19/1981 |
| BAH-1971 | Isa Bin Salman Al Khalifa | Bahrain | _BAXD | GFD | MSWRLD$ | Heart Attack | No | 3/6/1999 |
| KUW-1991 | Jaber III Al-Ahmad Al-Jaber Al-Sabah | Kuwait | _KWSED | GFD | MSWRLD$ | Cerebral Hemorrhage | Yes | 1/15/2006 |
| GHA-2009 | John Atta Mills | Ghana | IFFMGHL | Datastream | MSWRLD$ | Stroke | No | 7/24/2012 |
| AUL-1941-2 | John Curtin | Australia | AU34ORDD | GFD | Own | Heart Failure | Yes | 4/30/1945 |
| AUL-1932 | Joshep Aloysius Lyons | Australia | AU34ORDD | GFD | Own | Heart Attack | No | 4/7/1939 |
| HUN-1990 | Jozsef Antall | Hungary | BUXINDX | Datastream | MSWRLD$ | Cancer: Non-Hodgkin's Lymphoma | Yes | 12/12/1993 |
| ARG-1973-3 | Juan Domingo Perón | Argentina | _IBGD | GFD | MSWRLD$ | Heart Attack | No | 6/29/1974 |
| JPN-1998 | Keizö Obuchi | Japan | _TOPXD | GFD | MSWRLD$ | Stroke | Yes | 4/3/2000 |
| POL-2005 | Lech Kaczynski | Poland | _WIG20D | GFD | MSWRLD$ | Plane Crash | No | 4/10/2010 |
| ISR-1963 | Levi Eshkol | Israel | _TA100D | GFD | Own | Heart Attack | No | 2/26/1969 |
| ZAM-2002 | Levy Mwanawasa | Zambia | ZAMALSH | Datastream | MSWRLD$ | Stroke | No | 8/19/2008 |
| JPN-1978 | Masayoshi Ohira | Japan | _TOPXD | GFD | MSWRLD$ | Heart Attack | No | 6/12/1980 |
| JAM-1989 | Michael Manley | Jamaica | JMCOMPD | GFD | MSWRLD$ | Cancer: Prostate | Yes | 3/28/1992 |
| NEW-1972-2 | Norman Eric Kirk | New Zealand | _NZCID | GFD | MSWRLD$ | Heart Attack | No | 8/31/1974 |
| NOR-1976 | Odvar Nordli | Norway | MSNWAYL | Datastream | MSWRLD$ | Resigned: Health Reasons | Yes | 1/31/1981 |
| ARG-1981-1 | Roberto Eduardo Viola | Argentina | _IBGD | GFD | MSWRLD$ | Heart Failure | Yes | 11/21/1981 |
| NIG-1993-2 | Sani Abacha | Nigeria | _NGSEIND | GFD | MSWRLD$ | Heart Attack | No | 6/8/1998 |
| JPN-1956 | Tanzan Ishibashi | Japan | _TOPXD | GFD | Own | NA | Yes | 2/23/1957 |
| CZE-1918 | Tomás Garrigue Masaryk | Czechoslovakia | CZPRAGD | GFD | Own | Pneumonia | Yes | 12/14/1935 |
| NIG-2007 | Umaru Musa Yar'Adua | Nigeria | _NGSEIND | GFD | MSWRLD$ | Heart Failure | Yes | 2/9/2010 |
| CAN-1935 | W. L. Mackenzie King | Canada | CAXXMD | GFD | Own | Pneumonia | Yes | 11/15/1945 |
| USA-1921 | Warren Gamaliel Harding | United States | USNYTCOD | GFD | Own | Heart Attack | No | 8/2/1923 |
| UAE-1971 | Zayed bin Sultan Al Nahyan | United Arab Emirates | TOTMKAE | Datastream | MSWRLD$ | Ill Health | Yes | 11/2/2004 |

Notes: The first column indicates the ID used by Archigos to identify each leader. The second and third columns show the leader's name and country, respectively. The fourth and fifth columns display the ticker of the selected stock price series and its source respectively. The sixth column shows the world series used. The seventh column shows the reason of exit. The eighth column displays if the leader's exit is deemed as unsurprising or not. The ninth column displays the date of the exit.

# 5 Results

Historical investigation suggests that unexpected or “random” leader exits should impact equity prices, and the size of this effect depends on whether the exit is due to a sudden accident or not. For example, Figure 3 shows two dramatic types of unexpected exits: surprising deaths caused by accidents (heart attack, stroke, plane crash, or drowning) and unsurprising exits (all the other, primarily death due to a long-standing illness).

In each graph the dashed line represents the exact exit date. Panel (1) in Figure 3 presents the surprising exits of two leaders: Lech Kaczynski (Poland, died in a plane crash) and Norman E. Kirk (New Zealand, died of a sudden heart attack). On the other hand, Panel (2) shows the unsurprising exits of two other leaders: Andreas Papandreou (Greece, heart failure after a long bout with pneumonia) and Francisco Franco (Spain, heart failure following Parkinson disease).

In the case of Lech Kaczynski, we see a close association between the world market index and the local index in Poland throughout the days around the exit. At the time of the event, the local index shows a slight jump upwards (perhaps because of the end of his divisive and ineffective rule) preceded by a small decline. For Norman E. Kirk, the New Zealand’s stock index consistently outperformed the world index during the period around his exit. Prime Minister Kirk’s death, however, did not seem to affect the local stock index’s cumulative return. The cases in Figure 3 Panel (2) show a different pattern. Andreas Papandreou’s exit was associated to a small and short decline in the local index followed by a considerable jump (of around 3 percent points). Similarly, Francisco Franco’s exit was related to a jump (of around 12 percent points) in the local index up until 20 days after his death.


Figure 3: Cumulative return for individual leaders over a window of 61 calendar days. The starting point is 30 days before the exit. Each graph presents two series, the country and world stock indexes. The values displayed are relative to the first value in each series to facilitate comparisons.

Although these associations may be coincidental, they are part of the main pattern in our sample: overall, leader exits are associated to a *positive* cumulative abnormal return. As we will show, unsurprising exits drive this result as surprising exits are not systematically associated to abnormal returns different than zero. In what follows we present the detailed analysis leading to these conclusions. We study the effect of leader exits on abnormal returns using three sub-samples: The whole sample of unexpected exits, the sample of surprising exits, and the sample of unsurprising exits.

Table 2 shows our main results. Significance levels are computed based on the $Z$ statistic presented in Appendix 8.3, which under regular assumptions follows a Standard Normal

Distribution. Panel (1) presents the cumulative average abnormal return (CAAR) for the whole sample of unexpected exits. The CAAR is positive and significant for all 5 windows considered: [-3,3]; [-3,7]; [-3,15]; [-1,15]; and [-5,15]. The first number in each pair represents the bottom left bound of the window and the second represents the upper right bound, where 0 is the day of the exit. As Panel (1) of the table shows, stock markets' abnormal returns vary from 0.8% to 1.8% across these windows for the unexpected sample. Panel (2) presents the CAAR for leaders who exited surprisingly for each of the windows. The point estimate in each window is low and not statistically different from zero. On the other hand, for the sample of unsurprising exits, Panel (3) shows that the CAAR is positive and significantly different from zero in each window. CAARs in this case range from 1.3% to more than 3%.

Given that our sample is relatively small, we complement the $Z$-statistic used to test the null hypothesis that each CAAR is zero (defined in Appendix 8.3), with two different bootstrapped $p$-values based on the empirical distribution of the CAAR (see Appendix 8.4). The first one, from left to right, shows that the effect for unsurprising exits is significant but at lower levels than when computed with the $Z$ statistic. The $p$-values range from 7% to 15%. The second bootstrapped $p$-value, on the other hand, takes into account outliers by winsorizing them. In these cases, the results are quantitatively very similar to the ones first reported and confirm that the effect of unsurprising exits is statistically different from zero.

Table 2: Unexpected Exits - Cumulative Average Abnormal Return (CAAR)

Panel (1): CAAR - Unexpected Exits

| Window | Number of observations | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value | Winsorized $p$-Value |
|---|---|---|---|---|---|
| $[-3, 3]$ | 38 | 0.0082 | 0.1327 | 0.1473 | 0.0390 |
| $[-3, 7]$ | 38 | 0.0181** | 0.0201 | 0.0634 | 0.0026 |
| $[-3, 15]$ | 38 | 0.0177* | 0.0564 | 0.1270 | 0.0164 |
| $[-1, 15]$ | 38 | 0.0157 | 0.1200 | 0.1671 | 0.0271 |
| $[-5, 15]$ | 38 | 0.0171* | 0.0774 | 0.1700 | 0.0326 |

Panel (2): CAAR - Surprising Exits

| Window | Number of observations | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value | Winsorized $p$-Value |
|---|---|---|---|---|---|
| $[-3, 3]$ | 15 | 0.0010 | 0.7584 | 0.4846 | 0.7155 |
| $[-3, 7]$ | 15 | 0.0039 | 0.5955 | 0.3049 | 0.3722 |
| $[-3, 15]$ | 15 | -0.0008 | 0.8406 | 0.5245 | 0.5476 |
| $[-1, 15]$ | 15 | 0 | 0.7244 | 0.4919 | 0.6129 |
| $[-5, 15]$ | 15 | -0.0035 | 0.9281 | 0.5977 | 0.6706 |

Panel (3): CAAR - Unsurprising Exits

| Window | Number of observations | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value | Winsorized $p$-Value |
|---|---|---|---|---|---|
| $[-3, 3]$ | 23 | 0.0129** | 0.0292 | 0.1197 | 0.0061 |
| $[-3, 7]$ | 23 | 0.0274** | 0.0105 | 0.0725 | 0.0003 |
| $[-3, 15]$ | 23 | 0.0298*** | 0.0089 | 0.1004 | 0.0013 |
| $[-1, 15]$ | 23 | 0.0260** | 0.0224 | 0.1480 | 0.0023 |
| $[-5, 15]$ | 23 | 0.0306** | 0.0191 | 0.1273 | 0.0024 |

Notes: Each panel reports cumulative average abnormal returns (CAAR) over different windows as well as their corresponding $Z$ statistic and bootstrapped $p$-values. The whole sample of unexpected exits is presented in Panel (1) and it is then split into surprising (due to an accident) and unsurprising (due to long-standing ailment) exits in Panels (2) and (3) respectively. Column 4 presents the $p$-value, for the null $H_0 : CAAR = 0$, computed from the $Z$ statistic described in Appendix 8.3. Columns 5 and 6 show two alternative bootstrapped $p$-values, based on the empirical distribution of the CAAR, described in Appendix 8.4. Significance at the 10%, 5% and 1% are denoted by *, ** and ***, respectively, and based on the $Z$ statistic's $p$-value.

Figure 4 illustrates these results. It depicts the variation of the CAAR for each window through time, from window [-3,-3] to window [-3,15]. It shows that for surprising exits, the CAARs across windows linger around zero, and for unsurprising exits the CAARs increase to converge to roughly 3%.

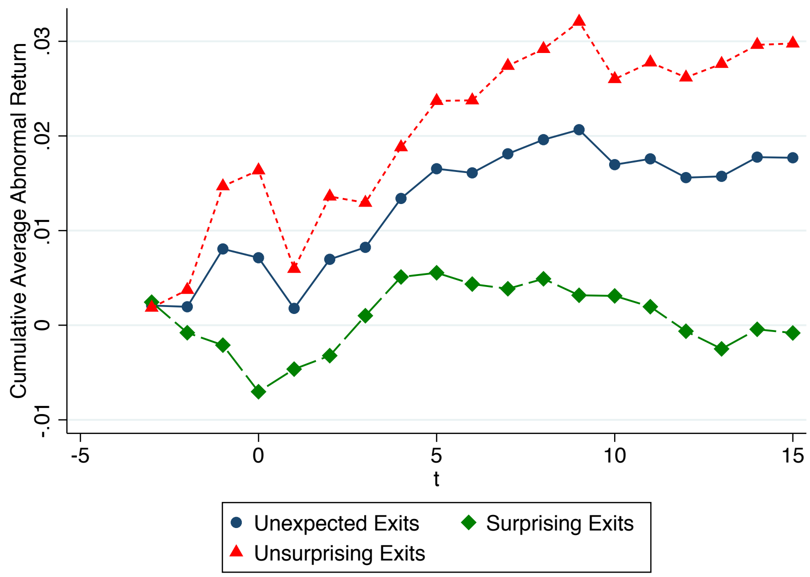



Figure 4: Accumulated average abnormal return day by day for unexpected, surprising and unsurprising exits. The starting point is 3 trading days before the exit and ranges from 3 to 15 trading days after.

In contrast, there is no relevant effect around regular exits. Table 3 shows the CAARs for the placebo group considering the same windows as before. The results are not statistically significant at any conventional level.

Table 3: Expected Exits - Cumulative Average Abnormal Return (CAAR)

| Window | Number of Observations | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value | Winsorized $p$-Value |
|---|---|---|---|---|---|
| $[-3, 3]$ | 157 | -0.0004 | 0.6340 | 0.5446 | 0.9130 |
| $[-3, 7]$ | 157 | 0.0028 | 0.7321 | 0.3041 | 0.2184 |
| $[-3, 15]$ | 157 | -0.0002 | 0.6282 | 0.5082 | 0.5167 |
| $[-1, 15]$ | 157 | -0.0038 | 0.1556 | 0.7370 | 0.9322 |
| $[-5, 15]$ | 157 | 0.0038 | 0.9454 | 0.2926 | 0.3555 |

Notes: Cumulative average abnormal returns (CAAR) over different windows for the placebo group as well as their corresponding $Z$ statistic and bootstrapped $p$-values. The 157 observations correspond to leaders that belong to the same countries contained in the main sample who lost power in a regular manner. $Z$ is the test statistic described in Appendix 8.3 for the null $H_0: \ CAAR = 0$. Significance at the 10%, 5% and 1% are denoted by $^{*}$, $^{**}$ and $^{***}$, respectively, and based on the $Z$ statistic's $p$-value. Column 5 and 6 show two alternative bootstrapped $p$-values described in Appendix 8.4.

These results indicate that not all transitions are alike and markets respond differently according to the nature of the exit. In particular, they seem to respond positively to indisposed leader (unsurprising) exits, but not to surprising leader exits. As noted by Jones and Olken (2005), the zero effect of surprising exits may be the result of averaging out the positive effect of bad leaders and the negative effect of good leaders. The histograms in Panel (1) of Figure 5 suggest this may be actually the case. These histograms show cumulative abnormal returns (CARs) in windows [-3,15] and [-5,15] for leaders who left office surprisingly. Both histograms show that CARs are evenly spread out to both sides of zero. However, when compared to the histograms in Panel (2), which are for CARs from unsurprising exits, we observe that the dispersion of CARs from surprising exists is relatively small compared to the one from unsurprising ones. Moreover, CARs for unsurprising exits are also more positive than negative for both windows.

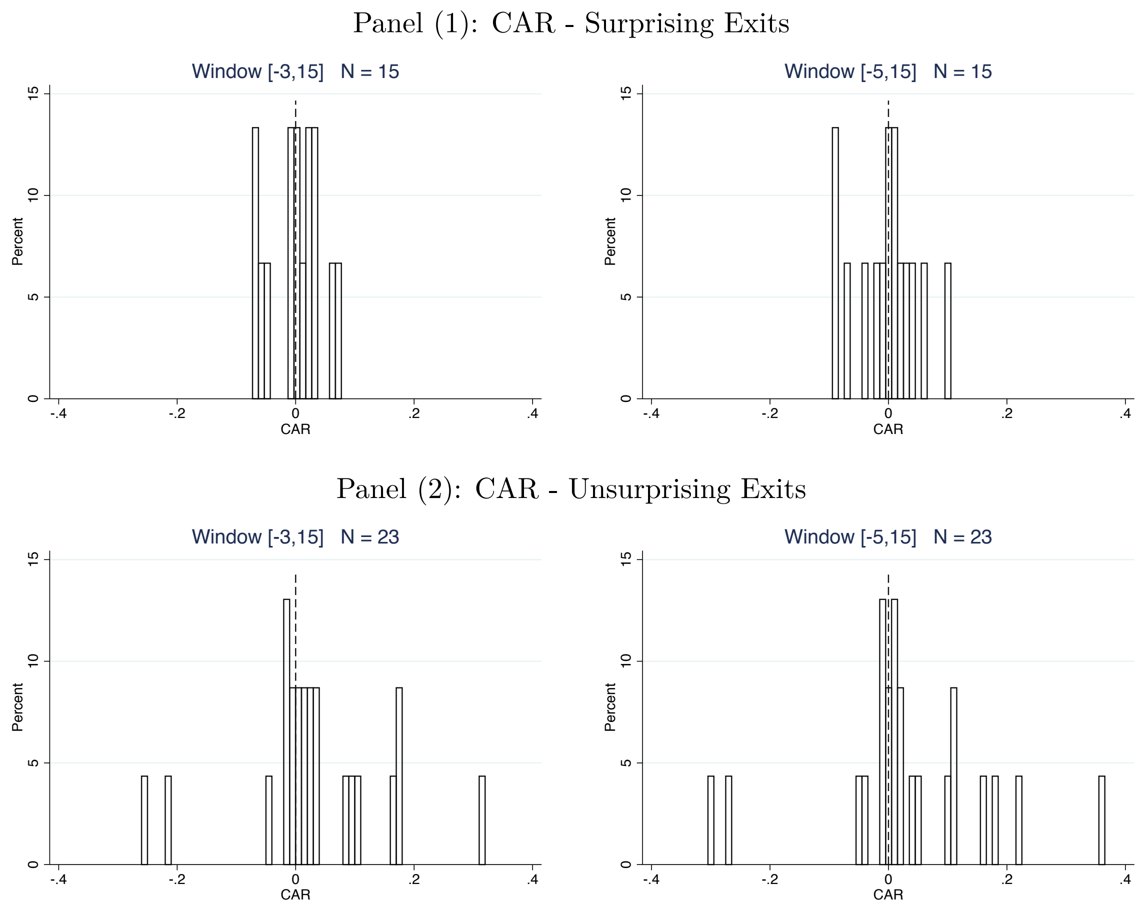



Figure 5: Histograms of cumulative abnormal returns (CAR) for both surprising and unsurprising exits. For each sample, we present histograms for two different windows. The first window starts 3 trading days before the exit and lasts until 15 trading days after. On the other hand, the second windows ranges from 5 trading days before the exit until 15 trading days after. The dashed vertical line lies over the day the exit took place.

We use the $K$ statistic described in section 3.2 to test whether CARs associated to surprising exits take on extreme values compared to their corresponding time-series counterparts. The $K$ statistic is large when, on average, the CAR around the event is extreme compared to surrounding *auxiliary* CARs. These auxiliary CARs are computed before and after the exit's CAR.[10] On the other hand, the $K$ statistic is low when the CAR around the exit is,

[10]Given the fixed length of the analysis period, the window's length used to compute the auxiliary CARs will determine how many of them will be available to compute the percentiles ranks, which are necessary to compute the $K$ statistic. In order to increase the number of CARs, we use windows covering a period of up to 11 trading days.

on average, similar to the median surrounding CAR.

Panel (1) in Table 4 shows that the value of the $K$ statistic varies between -1.495 and -0.314 and it is not significant at any relevant level for the set of surprising exits. As a result, we see no evidence to conclude that surprising exits lead to systematic time-series changes in cumulative abnormal returns. Unsurprising exits on the other hand, show a different pattern. Panel (2) shows that the $K$ statistic associated to unsurprising exits is positive and significantly different from zero. Values range from 1.042 to 1.923 and they are significant at the 1% level. This suggests that the effect of unsurprising exits is not only significant locally around the exit but that it is also significantly different from both previous and future behavior.

Table 4: Unexpected Exits - $K$ Statistic

Panel (1): $K$ Statistic - Surprising Exits

| Window | Total CARs | Average $K_{Surprising}$ | $p$-Value$_{Surprising}$ |
|---|---|---|---|
| $[-5, 5]$ | 22 | -0.730 | 0.881 |
| $[-3, 3]$ | 35 | -0.314 | 0.781 |
| $[-3, 7]$ | 22 | -1.069 | 0.960 |
| $[-1, 3]$ | 49 | -1.495 | 1 |

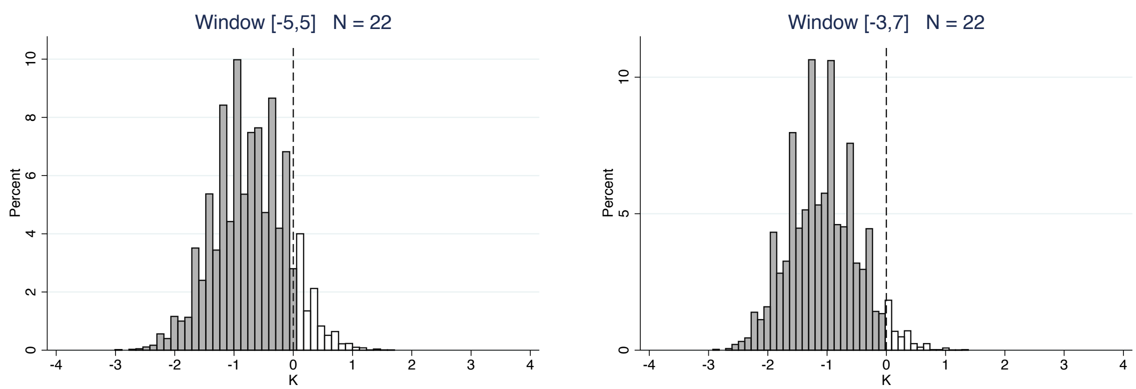
Panel (2): $K$ Statistic - Unsurprising Exits

| Window | Total CARs | Average $K_{Unsurprising}$ | $p$-Value$_{Unsurprising}$ |
|---|---|---|---|
| $[-5, 5]$ | 22 | 1.923 | $<$0.01 |
| $[-3, 3]$ | 35 | 1.181 | $<$0.01 |
| $[-3, 7]$ | 22 | 1.042 | $<$0.01 |
| $[-1, 3]$ | 49 | 1.235 | $<$0.01 |

Notes: Average $K$ statistic for different windows, for both surprising and unsurprising exits. The second column shows the number of non-overlapping CARs used. The analysis considers 251 trading days, starting 190 days before the exit until 60 days after. Average $K$ statistics were computed using Monte Carlo simulations as described in Appendix 8.5.

Given that our sample is relatively small, we opted to compute the empirical distribution of $K$ using Monte Carlo simulations. The histograms in Panel (1) of Figure 6 show that the distribution of $K$ from surprising exists is skewed to the left of zero. In contrast, histograms in Panel (2) of the figure show that the distribution of $K$ from unsurprising exits is skewed to the right.

Panel (1) $K$ Statistic - Surprising Exits




Panel (2): $K$ Statistic - Unsurprising Exits

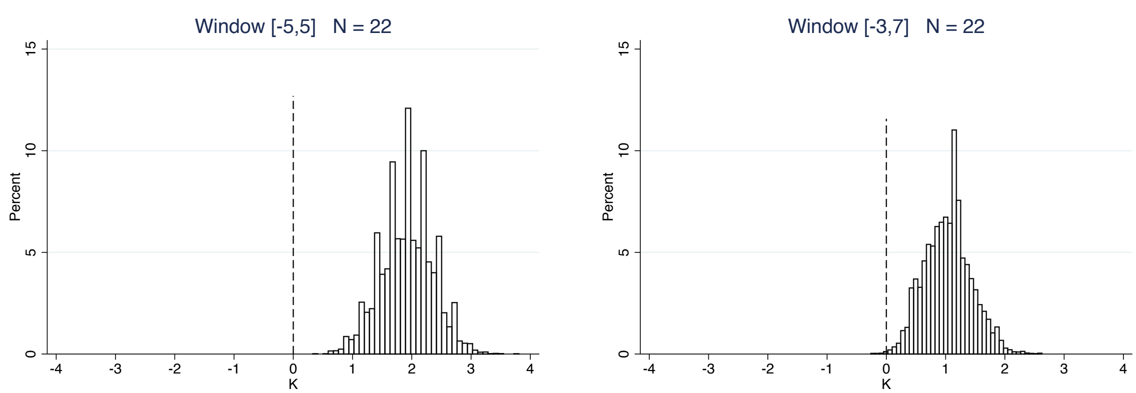



Figure 6: Histograms for both surprising and unsurprising exits of the $K$ statistic over different windows' lengths. The $K$ statistic is positive when a leader's CAR around his exit is extreme in comparison to cumulative abnormal returns in previous and subsequent non-overlapping windows. The analysis considers 251 trading days, starting 190 days before the exit until 60 days after. The dashed vertical line lies over 0. The distributions were obtained from Monte Carlo simulations as described in Appendix 8.5. Any column to the left of the line is shaded to make it easier to identify as a negative value.

We also study the dispersion of the CARs in the placebo group using the same procedure as before. The results of this analysis are shown in Table 5. The $K$ statistic is positive and significant for the different windows considered. This suggests that the CARs around the date of exit are different from the ones during the period before and after the event. However, this effect cancels out when calculating the cross-sectional average (i.e., the CAAR) as shown in Table 3.

Table 5: Expected Exits - $K$ Statistic

| Window | Total CARs | Average $K$ | $p$-Value |
|---|---|---|---|
| $[-5, 5]$ | 22 | 1.943 | $< 0.01$ |
| $[-3, 3]$ | 35 | 2.455 | $< 0.01$ |
| $[-3, 7]$ | 21 | 1.687 | $< 0.01$ |
| $[-1, 3]$ | 50 | 0.796 | 0.022 |

Notes: Average $K$ statistic for different windows, for expected exits. The second column shows the number of non-overlapping CARs used. The analysis considers 251 trading days, starting 167 days before the exit until 83 days after. Average $K$ statistics were computed using Monte Carlo simulations as described in Appendix 8.5.

Our results suggest that equity markets thrive (at least in the short run) when an indisposed leader exits, but they seem to adjust quickly after a surprising exit. In the following section we use our data to disentangle the mechanisms underlying this phenomenon.

## 5.1 Volatility of Returns

The second question we address in this paper is whether the volatility of returns changes around leader transitions, as this could explain the changes in stock market returns. We describe three measures for whether leaders' exits are associated to an increase in volatility. We argue that this is not the case for neither surprising nor unsurprising exits. Therefore, the positive and significant CAAR obtained in previous sections for unsurprising exits is most likely explained by an increase in expected dividends across firms and not by a shift in country risk. For more details on the relationship between these two channels see Appendix 8.6.

First, we use Bloom's (2009) criterion to label an exit as a *volatility shock* if the volatility of daily stock returns during the month of the exit is significantly higher than the volatility of adjacent months. Specifically, we compute the volatility of daily stock returns for 49 calendar months centered around each exit. Then, we compare the standardized volatility during the month of the exit with the 5% one-tailed critical value of a Normal distribution. Results are presented in Figure 7. The histogram shows the distribution of the standardized volatilities for all unexpected exits, as well as for unsurprising exits. As the figure shows, there are only 2 events that fulfill Bloom's criterion and both of them correspond to unsurprising exits.

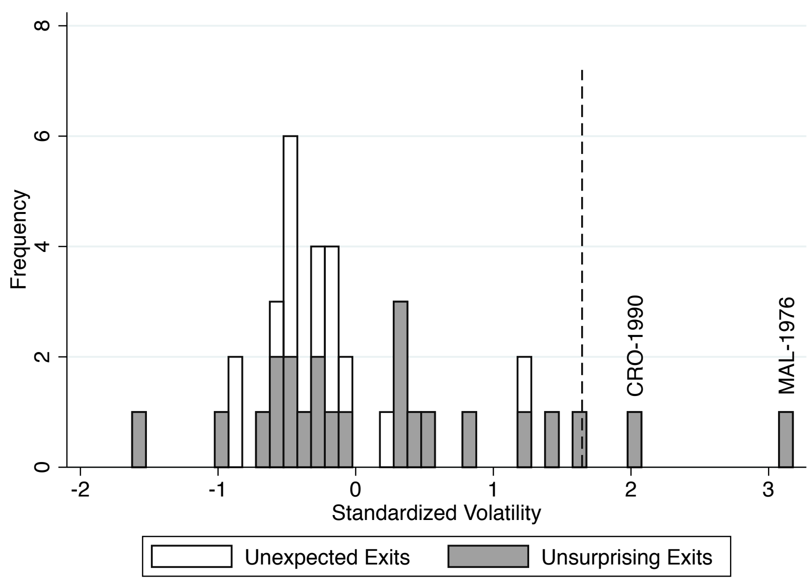



Figure 7: Frequency histogram of standardized volatilities. The histogram displays the standardized volatility of the month in which the exit takes place for both the whole sample of unexpected exits and unsurprising exits. The vertical dashed line shows a 1.65 threshold (5% one-tailed significance level). Any value laying on the right of this line corresponds to a *volatility shock*.

Second, we use the standard deviation of daily stock returns to assess whether leaders' exits affect the volatility of market indexes by comparing their values in the period immediately prior (pre) to the ones immediately after (post). Table 6 shows the average volatility of indexes returns 20, 60, and 100 days before and after leaders' exits, grouped by unexpected, surprising and unsurprising exits. Results show no significant differences between before and after volatilities for any of the samples. This is consistent with intuition, since a long-term shift in volatility is very uncommon in stock markets.

Third, we study variations in equities' betas before and after the events. Betas are a measure of systematic risk, which should be closely related to total risk, measured by volatilities. Table 7 shows 60, 100, and 200 days pre and post-exit betas and their differences. These betas are computed as in section 3.1 using the Scholes-Williams estimator. We use longer windows in comparison to the ones used to compute volatilities in order to obtain a better fit from OLS. Our results confirm that there is no significant difference between pre and post-betas in any of the samples.

Overall, these results suggest that unexpected exits are not generating a risk shift that could affect the county cost of capital. Therefore, positive and significant CAAR for unsurprising exits should be related to an increase in expected dividends across firms in the economy and not to a shift in risk.[11]

[11]This results are consistent with Pástor and Veronesi (2012). In their case, firm profits depend on the realization of the government policy, which in our case can be interpreted as the change of political regime due to the leader's exit.

Table 6: Effect of Unexpected Exits - Volatility

Panel (1): Volatility - Unexpected Exits

| Days Around Exit (n) | Number of Observations | $\sigma_{PRE[-n,-1]}$ | $\sigma_{POST[1,n]}$ | $\triangle\sigma_{POST-PRE}$ | $p$-Value $H_a : \triangle\sigma < 0$ | $p$-Value $H_a : \triangle\sigma > 0$ |
|---|---|---|---|---|---|---|
| 20 | 38 | 0.008 | 0.008 | 0.000 | 0.475 | 0.525 |
| 60 | 38 | 0.009 | 0.009 | 0.000 | 0.555 | 0.445 |
| 100 | 37 | 0.008 | 0.009 | 0.000 | 0.640 | 0.360 |

Panel (2): Volatility - Surprising Exits

| Days Around Exit (n) | Number of Observations | $\sigma_{PRE[-n,-1]}$ | $\sigma_{POST[1,n]}$ | $\triangle\sigma_{POST-PRE}$ | $p$-Value $H_a : \triangle\sigma < 0$ | $p$-Value $H_a : \triangle\sigma > 0$ |
|---|---|---|---|---|---|---|
| 20 | 15 | 0.009 | 0.009 | 0.000 | 0.612 | 0.388 |
| 60 | 15 | 0.010 | 0.011 | 0.001 | 0.680 | 0.320 |
| 100 | 15 | 0.009 | 0.010 | 0.001 | 0.701 | 0.299 |

Panel (3): Volatility - Unsurprising Exits

| Days Around Exit (n) | Number of Observations | $\sigma_{PRE[-n,-1]}$ | $\sigma_{POST[1,n]}$ | $\triangle\sigma_{POST-PRE}$ | $p$-Value $H_a : \triangle\sigma < 0$ | $p$-Value $H_a : \triangle\sigma > 0$ |
|---|---|---|---|---|---|---|
| 20 | 23 | 0.007 | 0.007 | 0.000 | 0.308 | 0.692 |
| 60 | 23 | 0.008 | 0.007 | 0.000 | 0.272 | 0.728 |
| 100 | 22 | 0.008 | 0.008 | 0.000 | 0.433 | 0.567 |

Notes: Cross-sectional average volatility over different time periods for unexpected, surprising and unsurprising exits. The volatility is computed using daily returns in windows of 20, 60 and 100 trading days for both the period before the exit $[-n, -1]$ and the period after $[1, n]$, where 0 is the day of the exit. The difference between the post and pre-exit value is displayed in the fifth column. Columns 6 and 7 test the equality of the post and pre-exit averages. The former shows the $p$-Value under the alternative hypothesis, $H_a : \triangle\sigma < 0$. The latter shows the $p$-Value under the alternative hypothesis, $H_a : \triangle\sigma > 0$.

Table 7: Unexpected Exits - Betas

Panel (1): Betas - Unexpected Exits

| Days Around Exit (n) | Number of Observations | $\beta_{PRE[-n,-1]}$ | $\beta_{POST[1,n]}$ | $\triangle\beta_{POST-PRE}$ | $p$-Value | |
|---|---|---|---|---|---|---|
| | | | | | $H_a:\triangle\beta<0$ | $H_a:\triangle\beta>0$ |
| 60 | 37 | 0.309 | 0.473 | 0.163 | 0.852 | 0.148 |
| 100 | 36 | 0.287 | 0.455 | 0.168 | 0.883 | 0.117 |
| 200 | 36 | 0.338 | 0.349 | 0.011 | 0.535 | 0.465 |

Panel (2): Betas - Surprising Exits

| Days Around Exit (n) | Number of Observations | $\beta_{PRE[-n,-1]}$ | $\beta_{POST[1,n]}$ | $\triangle\beta_{POST-PRE}$ | $p$-Value | |
|---|---|---|---|---|---|---|
| | | | | | $H_a:\triangle\beta<0$ | $H_a:\triangle\beta>0$ |
| 60 | 14 | 0.301 | 0.260 | -0.042 | 0.423 | 0.577 |
| 100 | 14 | 0.339 | 0.284 | -0.055 | 0.392 | 0.608 |
| 200 | 14 | 0.348 | 0.224 | -0.124 | 0.266 | 0.734 |

Panel (3): Betas - Unsurprising Exits

| Days Around Exit (n) | Number of Observations | $\beta_{PRE[-n,-1]}$ | $\beta_{POST[1,n]}$ | $\triangle\beta_{POST-PRE}$ | $p$-Value | |
|---|---|---|---|---|---|---|
| | | | | | $H_a:\triangle\beta<0$ | $H_a:\triangle\beta>0$ |
| 60 | 23 | 0.314 | 0.602 | 0.288 | 0.909 | 0.091 |
| 100 | 22 | 0.253 | 0.564 | 0.310 | 0.945 | 0.055 |
| 200 | 22 | 0.332 | 0.429 | 0.097 | 0.720 | 0.280 |

Notes: Cross-sectional average beta over different time periods for unexpected, surprising and unsurprising exits. Beta is computed using daily returns in windows of 60, 100 and 200 trading days for both the period before the exit $[-n,-1]$ and the period afterwards $[1,n]$, where 0 is the day of exit. In order to account for non-synchronous trading, the market model parameters are computed using the method proposed by Scholes and Williams (1977). The difference between the post and pre-exit values is displayed in the fifth column. Columns 6 and 7 test the equality of the post and pre-exit averages. The former shows the $p$-Value under the alternative hypothesis, $H_a:\triangle\beta<0$. The latter shows the $p$-Value under the alternative hypothesis, $H_a:\triangle\beta>0$.

We then study whether the exits in the placebo group can be deemed as *volatility shocks* or not. According to the criteria described in section 3.3 there is a total of 17 of these cases out of a total of 157 entries (i.e., 10.8%). Figure 8 shows a histogram with the standardized volatilities.

We also study the changes in volatilities and betas before and after regular exits take place. Panel (1) of Table 8 shows average volatilities for the same windows in Table 6 (20, 60, and 100 days before and after the leaders' exits). Panel (2) on the other hand, shows the Scholes-Williams estimator before and after the events take place for the same windows as in Table 7 (60, 100 and 200 trading days for both the period before the exit and the period afterwards). In both cases, the results show no significant variations between before and after.

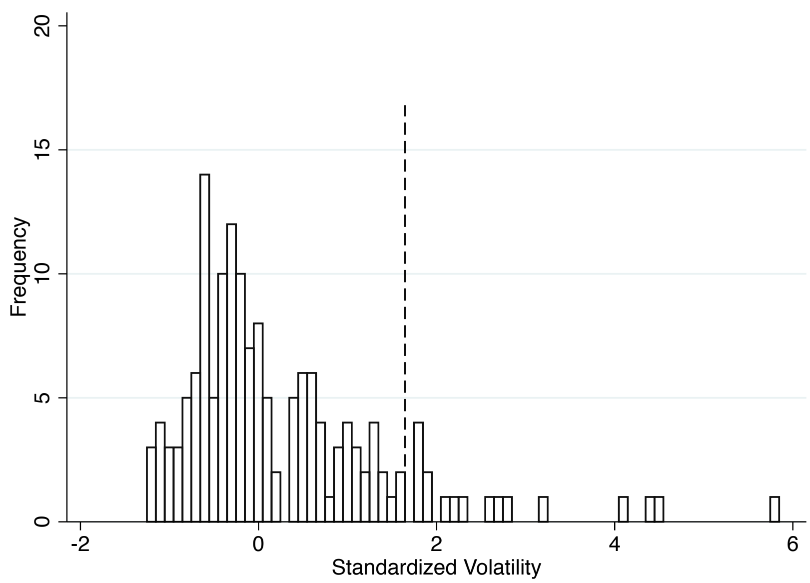



Figure 8: Frequency histogram of standardized volatilities. The histogram displays the standardized volatility of the month in which the exit takes place for the placebo sample. The vertical dashed line shows a 1.65 threshold (5% one-tailed significance level). Any value laying on the right of this line corresponds to a *volatility shock*.

Table 8: Effect of Expected Exits - Volatility and Betas

Panel (1): Volatility - Expected Exits

| Days Around Exit (n) | Number of Observations | $\sigma_{PRE[-n,-1]}$ | $\sigma_{POST[1,n]}$ | $\triangle\sigma_{POST-PRE}$ | $p$-Value $H_a : \triangle\sigma < 0$ | $p$-Value $H_a : \triangle\sigma > 0$ |
|---|---|---|---|---|---|---|
| 20 | 157 | 0.016 | 0.017 | 0.001 | 0.716 | 0.284 |
| 60 | 157 | 0.015 | 0.016 | 0.001 | 0.835 | 0.165 |
| 100 | 156 | 0.015 | 0.016 | 0.001 | 0.761 | 0.239 |

Panel (2): Beta - Expected Exits

| Days Around Exit (n) | Number of Observations | $\beta_{PRE[-n,-1]}$ | $\beta_{POST[1,n]}$ | $\triangle\beta_{POST-PRE}$ | $p$-Value $H_0 : \triangle\beta < 0$ | $p$-Value $H_0 : \triangle\beta > 0$ |
|---|---|---|---|---|---|---|
| 60 | 156 | 0.658 | 0.716 | 0.058 | 0.779 | 0.221 |
| 100 | 156 | 0.699 | 0.721 | 0.022 | 0.630 | 0.370 |
| 200 | 156 | 0.729 | 0.738 | 0.009 | 0.564 | 0.436 |

Notes: Cross-sectional average volatility over different time periods for the placebo group. The volatility is computed using daily returns in windows of 20, 60 and 100 trading days for both the period before the exit $[-n,-1]$ and the period after $[1,n]$, where 0 is the day of the exit The difference between the post and pre-exit value is displayed in the fifth column. Columns 6 and 7 test the equality of the post and pre-exit averages. The former shows the $p$-Value under the alternative hypothesis, $H_a : \triangle\sigma < 0$. The latter shows the $p$-Value under the alternative hypothesis, $H_a : \triangle\sigma > 0$. Panel (2) displays the cross-sectional average beta over different time periods for the placebo group. Beta is computed using daily returns in windows of 60, 100 and 200 trading days for both the period before the exit $[-n,-1]$ and the period afterwards $[1,n]$, where 0 is the day of exit. In order to account for non-synchronous trading, the market model parameters are computed using the method proposed by Scholes and Williams (1977). The difference between the post and pre-exit values is displayed in the fifth column. Columns 6 and 7 test the equality of the post and pre-exit averages. The former shows the $p$-Value under the alternative hypothesis, $H_a : \triangle\beta < 0$. The latter shows the $p$-Value under the alternative hypothesis, $H_a : \triangle\beta > 0$.

## 5.2 Interactions with Level of Democratization

The results above suggest a causal effect of leader's exit on return levels. However, the institutional arrangement in place may affect the extent to which leaders matter. Given the results in Jones and Olken (2005), we expect that the positive market reaction to unsurprising exits is mainly explained by ill autocratic leaders, as opposed to democratic leaders, who died in office. We conduct the event analysis described in section 3.1 for two different sets of leaders, splitting the sample of unexpected exits according to whether a country is considered a democracy or not.

We use the variable POLITY2 in the PolityIV (Marshall and Jaggers, 2007) database to classify the countries in our sample accordingly. POLITY2 ranges from -10 to +10 where the former indicates a strongly democratic regimen and the latter a strongly autocratic one. The entries in Table 9 compare leaders whose countries receive a negative or zero score ("autocrats") with those leaders whose countries receive a positive score ("democrats"). This criterion coincides with the one used by Besley et al. (2011) and Persson and Tabellini (2006). The results indicate that autocrats' exits have a strong positive effect on abnormal returns overall. The magnitude of this effect is substantial (around 8%) and driven by those who left office after health problems.

Table 9: Interactions With Type of Political Regime - CAAR

Panel (1): CAAR - Unexpected Exits

| | Autocrats (Polity IV) | | | | Democrats (Polity IV) | | | |
|---|---|---|---|---|---|---|---|---|
| Window | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value |
| $[-3,3]$ | 11 | 0.040*** | <0.01 | <0.01 | 26 | -0.005 | 0.7730 | 0.7789 |
| $[-3,7]$ | 11 | 0.072*** | <0.01 | <0.01 | 26 | -0.004 | 0.8800 | 0.6797 |
| $[-3,15]$ | 11 | 0.090*** | <0.01 | <0.01 | 26 | -0.012 | 0.5740 | 0.8625 |
| $[-1,15]$ | 11 | 0.091*** | <0.01 | <0.01 | 26 | -0.016 | 0.3980 | 0.9356 |
| $[-5,15]$ | 11 | 0.092*** | <0.01 | <0.01 | 26 | -0.014 | 0.6370 | 0.8478 |

Panel (2): CAAR - Surprising Exits

| | Autocrats (Polity IV) | | | | Democrats (Polity IV) | | | |
|---|---|---|---|---|---|---|---|---|
| Window | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value |
| $[-3,3]$ | 4 | 0.008 | 0.4560 | 0.1526 | 11 | -0.001 | 0.4190 | 0.5958 |
| $[-3,7]$ | 4 | 0.022 | 0.1940 | <0.01 | 11 | -0.003 | 0.8710 | 0.6713 |
| $[-3,15]$ | 4 | 0.036 | 0.1370 | <0.01 | 11 | -0.014 | 0.2580 | 0.9417 |
| $[-1,15]$ | 4 | 0.037 | 0.1780 | <0.01 | 11 | -0.013 | 0.2210 | 0.9759 |
| $[-5,15]$ | 4 | 0.042 | 0.1440 | <0.01 | 11 | -0.013 | 0.2210 | 0.9796 |

Panel (3): CAAR - Unsurprising Exits

| | Autocrats (Polity IV) | | | | Democrats (Polity IV) | | | |
|---|---|---|---|---|---|---|---|---|
| Window | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value |
| $[-3,3]$ | 7 | 0.058*** | <0.01 | <0.01 | 15 | -0.007 | 0.7540 | 0.785 |
| $[-3,7]$ | 7 | 0.101*** | <0.01 | <0.01 | 15 | -0.005 | 0.9530 | 0.6375 |
| $[-3,15]$ | 7 | 0.121*** | <0.01 | <0.01 | 15 | -0.011 | 0.8190 | 0.7158 |
| $[-1,15]$ | 7 | 0.123*** | <0.01 | <0.01 | 15 | -0.018 | 0.9470 | 0.8368 |
| $[-5,15]$ | 7 | 0.121*** | <0.01 | <0.01 | 15 | -0.010 | 0.8230 | 0.6542 |

Notes: Each panel reports the cumulative average abnormal return (CAAR) over different windows for unexpected, surprising and unsurprising exits. Each panel is split by the country's level of democratization. The level of democratization is determined using the variable POLITY2 in the PolityIV database. Democrats are defined as those leaders who rule in a country with a value higher than 0. Autocrats, on the other hand, are defined as those leaders who rule in a country with a value smaller than or equal to 0. $Z$ is the test statistic described in Appendix 8.3 for the null $H_0: CAAR = 0$. Significance at the 10%, 5% and 1% are denoted by $^{*}$, $^{**}$ and $^{***}$, respectively, and based on the $Z$ statistic's $p$-value. Columns 5 and 10 show bootstrapped $p$-Values as described in Appendix 8.4. The CARs are not winsorized in this analysis due to the small number of observations.

## 5.3 Interactions with Leader's Educational Level

Our previous results suggest that health issues seem to induce expectations in the market of an ineffective ruling. Therefore, we should expect that a leader's human capital may also affect those expectations and ultimately market returns on the event of his or her exit. Recent literature has studied the effect of the leader's education in the country's growth and firm's performance (e.g., Besley et al., 2011; Nguyen and Nielsen, 2010). Following these authors, in this section, we study the relevance of this variable.

We classify the educational attainment of each one of our leaders using a scale similar to Ludwig (2002): 1) illiterate, 2) literate without formal education, 3) primary education, 4) high/secondary school, 5) post-secondary no-college (including military formation), 6) college degree, 7) master's degree, and 8) doctorate. We are able to hand collect this information for 35 out of 38 entries in our sample. Due to the somewhat reduced sample size we split it in only two groups, those with high education (a college or higher degree) and those with low.

The results in Table 10 show evidence that abnormal returns are significantly positive when leaders with low education exit from office. The magnitude of this effect is substantial (around 6% for unexpected exits) and driven by relatively uneducated leaders who exit office after an illness. In the latter case, the effect increases to around 10%.

Table 10: Interactions With Leader's Education - CAAR

Panel (1): CAAR - Unexpected Exits

| | Education<6 | | | | Education≥6 | | | |
|---|---|---|---|---|---|---|---|---|
| Window | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value |
| $[-3, 3]$ | 12 | 0.029 | 0.2011 | <0.01 | 23 | -0.004 | 0.7039 | 0.7575 |
| $[-3, 7]$ | 12 | 0.054*** | 0.0086 | <0.01 | 23 | -0.002 | 0.6448 | 0.5757 |
| $[-3, 15]$ | 12 | 0.057** | 0.0325 | <0.01 | 23 | -0.008 | 0.9122 | 0.7241 |
| $[-1, 15]$ | 12 | 0.062** | 0.0250 | <0.01 | 23 | -0.011 | 0.8196 | 0.8276 |
| $[-5, 15]$ | 12 | 0.061** | 0.0283 | <0.01 | 23 | -0.011 | 0.8436 | 0.7742 |

Panel (2): CAAR - Surprising Exits

| | Education<6 | | | | Education≥6 | | | |
|---|---|---|---|---|---|---|---|---|
| Window | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value |
| $[-3, 3]$ | 6 | 0.004 | 0.432 | 0.4296 | 7 | -0.007 | 0.617 | 0.9425 |
| $[-3, 7]$ | 6 | 0.006 | 0.895 | 0.3050 | 7 | -0.003 | 0.831 | 0.7032 |
| $[-3, 15]$ | 6 | -0.002 | 0.616 | 0.5339 | 7 | -0.010 | 0.535 | 0.9066 |
| $[-1, 15]$ | 6 | -0.001 | 0.721 | 0.5240 | 7 | -0.006 | 0.492 | 0.8146 |
| $[-5, 15]$ | 6 | 0 | 0.831 | 0.5091 | 7 | -0.018 | 0.451 | 0.9743 |

Panel (3): CAAR - Unsurprising Exits

| | Education<6 | | | | Education≥6 | | | |
|---|---|---|---|---|---|---|---|---|
| Window | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value | N | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value |
| $[-3, 3]$ | 6 | 0.054*** | 0.0095 | <0.01 | 16 | -0.003 | 0.4317 | 0.6395 |
| $[-3, 7]$ | 6 | 0.101*** | 0.0001 | <0.01 | 16 | -0.001 | 0.6807 | 0.5210 |
| $[-3, 15]$ | 6 | 0.116*** | 0.0004 | <0.01 | 16 | -0.006 | 0.5873 | 0.6224 |
| $[-1, 15]$ | 6 | 0.124*** | 0.0004 | <0.01 | 16 | -0.014 | 0.8562 | 0.7889 |
| $[-5, 15]$ | 6 | 0.121*** | 0.0009 | <0.01 | 16 | -0.009 | 0.7931 | 0.6416 |

Notes: Each panel reports the cumulative average abnormal return (CAAR) over different windows for unexpected, surprising and unsurprising exits. Each panel is split by the leader's educational attainment. The whole sample contains 35 entries and it is then split into two groups containing 13 and 22 observations. Educational attainment is classified using a scale similar to Ludwig (2002) that ranges from 1 to 8 where the former indicates an illiterate leader and the latter indicates that the leader had a doctorate. College education (coded as 6) is used as a threshold to distinguish between well-educated leaders from those less educated. $Z$ is the test statistic described in Appendix 8.3 for the null $H_0: CAAR = 0$. Significance at the 10%, 5% and 1% are denoted by *, ** and ***, respectively, and based on the $Z$ statistic's $p$-value. Columns 5 and 10 show bootstrapped $p$-Values as described in Appendix 8.4. The CARs are not winsorized in this analysis due to the small number of observations.

# 6 Rumors about the Leader's Health

For most of the unsurprising exits, the leader's health condition was public knowledge before his death. In these cases, the market should have reacted when the rumors about his deteriorating health started. In this section, we apply the same analysis described in sections 5 and 5.1 to the event in which a string of rumors started appearing in the news. We are interested in whether the market responds to news about the national leader's health before his or her exit from office.

## 6.1 Data

We use LexisNexis Academic to search for news containing rumors or information about each leader's health in the unsurprising subgroup (for a similar procedure see Fisman, 2001). This database provides access to full-text news in both English and non-English sources. The latter are displayed translated to English.

In our search, we use three sets of words that must be jointly present somewhere in the news articles retrieved by LexisNexis. In the first set, we specify that either the leader's first or last name must be present. In the second set, at least one of the following must appear in the results: the country's name, the ruler's title (such as "prime minister" or "king") or the word "leader". In the third set, we required one of the following words: "ill", "diseased", "health", "illness" or "sick". We restrict the results to newspapers and hand collect the date of the first article concerning a rumor of the leader's health. We were not able to find any news concerning leaders that lost power before 1970.[12]

In the case of David Thompson for example, we found the following extract published May 15, 2010 among the search results:

> David Thompson says he has been suffering from stomach pains since early

[12]Due to this limitations we were unable to consider Franklin D. Roosevelt, Tomas Garrigue Masaryk, W. L. Mackenzie King, Tanzan Ishibashi, Hayato Ikeda and John Curtin in this analysis.

March.

While searching for rumors regarding Francisco Franco Bahamonde's health, on the other hand, we found an article published on July 10, 1974 with the following extract:

> Gen. Franco of Spain has been hospitalized for phlebitis. Study indicates that about 1/2 of those who suffer from phlebetis are hospitalized at some time and that 21% suffer from some long-term ill effects. Condition can lead to death, although fatalities are uncommon.

In total we were able to find information for 14 out of the 23 national leaders who left office in an unsurprising manner. Table 11 shows the list.

Table 11: Rumors Data

| ID | Name | Country | Reason of Exit | Date of Rumor |
|---|---|---|---|---|
| ISR-2001 | Ariel Sharon | Israel | Stroke | 12/19/2005 |
| TAW-1950 | Chiang Kai-Shek | Taiwan | Kidney Failure | 9/1/1972 |
| BAR-2008 | David Thompson | Barbados | Cancer: Pancreatic | 5/15/2010 |
| CHN-1980 | Deng Xiaoping | China | Parkinson Disease | 12/25/1996 |
| SPN-1939-2 | Francisco Franco Bahamonde | Spain | Parkinson Disease | 7/10/1974 |
| CRO-1990 | Franjo Tudjman | Croatia | Cancer: Stomach | 3/12/1999 |
| JOR-1952 | Hussein Bin Talal El-Hashim | Jordan | Cancer: Non-Hodgkin's Lymphoma | 8/26/1992 |
| MAL-1976 | Hussein Bin Onn | Malaysia | Heart Attack | 2/8/1981 |
| KUW-1991 | Jaber III Al-Ahmad Al-Jaber Al-Sabah | Kuwait | Cerebral Hemorrhage | 9/22/2001 |
| HUN-1990 | Jozsef Antall | Hungary | Cancer: Non-Hodgkin's Lymphoma | 10/5/1993 |
| JPN-1998 | Keizö Obuchi | Japan | Stroke | 4/3/2000 |
| JAM-1989 | Michael Manley | Jamaica | Cancer: Prostate | 3/7/1992 |
| NOR-1976 | Odvar Nordli | Norway | Resigned: Health Reasons | 1/31/1981 |
| NIG-2007 | Umaru Musa Yar'Adua | Nigeria | Heart Failure | 9/1/2008 |

Notes: The first column indicates the ID used by Archigos to identify each observation. The second and third columns show the leader's name and country, respectively. The fourth column shows the reason why the leader died or resigned. The fifth column displays the date of the first rumor concerning the leader's health.

## 6.2 Results

The results in Table 12 are consistent with a negative stock market reaction due to the rumors. In all the windows considered, cumulative abnormal returns are significantly negative with values around $-5\%$. Additionally, Table 13 shows that the market's behavior around the rumor is statistically different from the one displayed historically. The $K$ statistic is positive and statistically significant for almost all windows. This together with the positive reaction due to the posterior exit of these leaders (shown in previous sections) is consistent with a drop and rebound in stock market returns. Markets react adversely to the rumors and take precautions to withstand the period during which the leader will not be able to fulfill his duties thoroughly. Then, when the head of state's spell ends due to a complication of his illness, the market reacts positively as it lies in wait for the successor. In other words, since the exiting leader is seriously ill, the market expects the successor to perform better and the expected equity value to be higher. This seems to suggest that markets are more resilient to surprising exits, due to the tragic accidental death of a national leader, than to news about leaders' health complications. This could be explained by the uncertainty in the quality of the successor, in contrast to the quality of the leader leaving office in a surprising manner.

Table 12: Rumors of Possible Exits - Cumulative Average Abnormal Return (CAAR)

| Window | Number of Observations | CAAR | $Z$ $p$-Value | Bootstrapped $p$-Value | Winsorized $p$-Value |
|---|---|---|---|---|---|
| $[-9, 6]$ | 14 | -0.0492** | 0.0260 | 0.0154 | 0.0184 |
| $[-9, 7]$ | 14 | -0.0514** | 0.0390 | 0.0250 | 0.0259 |
| $[-9, 8]$ | 14 | -0.0535** | 0.0350 | 0.0180 | 0.0196 |
| $[-9, 9]$ | 14 | -0.0518* | 0.0570 | 0.0256 | 0.0202 |
| $[-10, 6]$ | 14 | -0.0489** | 0.0410 | 0.0174 | 0.0213 |
| $[-10, 7]$ | 14 | -0.0510* | 0.0580 | 0.0283 | 0.0281 |
| $[-10, 8]$ | 14 | -0.0532* | 0.0520 | 0.0215 | 0.0236 |
| $[-10, 9]$ | 14 | -0.0515* | 0.0800 | 0.0300 | 0.0236 |
| $[-10, 10]$ | 14 | -0.0535* | 0.0560 | 0.0172 | 0.0111 |

Notes: Cumulative average abnormal return (CAAR) over different windows around the date in which the first rumor was published as well as their corresponding $Z$ statistic and bootstrapped $p$-values. The 15 observations correspond to a subsample of unsurprising exits. $Z$ is the test statistic described in Appendix 8.3 for the null $H_0 : CAAR = 0$. Significance at the 10%, 5% and 1% are denoted by *, ** and ***, respectively, and based on the $Z$ statistic's $p$-value. Column 5 and 6 show two alternative bootstrapped $p$-values described in Appendix 8.4.

The intervals of trading days considered while studying the effect of rumors are different and slightly longer than the ones used to study the effect of unexpected exits. The main difference lies on the number of trading days considered in the period before the event takes place. One of the reasons to do this is that rumors might have a build-up period before being published. The second reason is that the sources for some of the rumors, specially for older leaders from less developed countries, came from large international newspapers. In these cases, it is likely that local media covered the news earlier, generating a lag with respect to our sources.

Table 13: Rumors of Possible Exits - $K$ Statistic

| Window | Total CARs | Average $K$ | $p$-Value |
|---|---|---|---|
| $[-9, 6]$ | 15 | 0.405 | 0.230 |
| $[-9, 7]$ | 14 | 1.408 | <0.01 |
| $[-9, 8]$ | 13 | 1.603 | <0.01 |
| $[-9, 9]$ | 13 | 2.094 | <0.01 |
| $[-9, 10]$ | 11 | 1.316 | 0.018 |
| $[-10, 6]$ | 14 | 1.331 | <0.01 |
| $[-10, 7]$ | 13 | 1.135 | 0.031 |
| $[-10, 8]$ | 13 | 1.806 | <0.01 |
| $[-10, 9]$ | 11 | 2.425 | <0.01 |
| $[-10, 10]$ | 11 | 1.599 | <0.01 |

Notes: Average $K$ statistic for different windows around the date of the first rumor concerning the leader's health. The second column shows the number of non-overlapping CARs used. The analysis considers 251 trading days, starting 106 days before the publication until 144 days after. Average $K$ statistics were computed using Monte Carlo simulations as described in Appendix 8.5.

### 6.2.1 Volatility of returns

As we did with the date of exit, we look for a change in volatility using three different, but complementary, procedures. First, we identify any exit that could be classified as a *volatility shock* according to Bloom's (2009) paper. Figure 9 shows the results of this analysis and it suggests that most of the events cannot be classified as such. Second, we study the market's volatility around the rumor's date. Panel (1) in Table 14 shows the results. There are no statistical differences between the market's volatility before and after the dates in which the rumors started. Finally, we estimate the betas for different windows before and after the rumor's date and obtain similar results. As Panel (2) in Table 14 presents, there is no significant difference between the betas before and after the rumors. Overall, this evidence leads us to believe that the negative and significant CAAR associated to the rumors is not caused by market uncertainty (volatility) but rather by a decrease in expected future cash flows.

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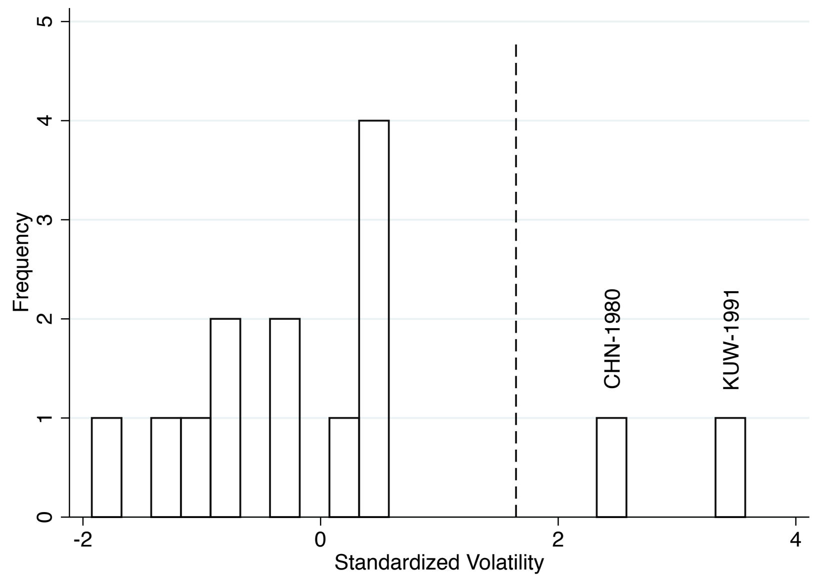


Figure 9: Frequency histogram of standardized volatilities. The histogram displays the standardized volatility of the month in which the rumor is published. The vertical dashed line shows a 1.65 threshold (5% one-tailed significance level). Any value laying on the right of this line corresponds to a *volatility shock*

Table 14: Rumors of Possible Exits - Volatility and Beta

Panel (1): Volatility - Rumors

| Days Around Rumor (n) | Number of Observations | $\sigma_{PRE[-n,-1]}$ | $\sigma_{POST[1,n]}$ | $\triangle\sigma_{POST-PRE}$ | $p$-Value | |
|---|---|---|---|---|---|---|
| | | | | | $H_a : \triangle\sigma < 0$ | $H_a : \triangle\sigma > 0$ |
| 20 | 14 | 0.015 | 0.013 | -0.002 | 0.331 | 0.669 |
| 60 | 14 | 0.015 | 0.013 | -0.002 | 0.272 | 0.728 |
| 100 | 14 | 0.016 | 0.014 | -0.001 | 0.337 | 0.663 |

Panel (2): Beta - Rumors

| Days Around Rumor (n) | Number of Observations | $\beta_{PRE[-n,-1]}$ | $\beta_{POST[1,n]}$ | $\triangle\beta_{POST-PRE}$ | $p$-Value | |
|---|---|---|---|---|---|---|
| | | | | | $H_0 : \triangle\beta < 0$ | $H_0 : \triangle\beta > 0$ |
| 60 | 14 | 0.331 | 0.240 | -0.091 | 0.328 | 0.672 |
| 100 | 14 | 0.373 | 0.436 | 0.063 | 0.608 | 0.392 |
| 200 | 13 | 0.429 | 0.400 | -0.029 | 0.450 | 0.550 |

Notes: Panel (1) shows the cross-sectional average volatility over different time periods around the date in which the first rumor concerning the leader's health was published. The volatility is computed using daily returns in windows of 20, 60 and 100 trading days for both the period before the exit $[-n, -1]$ and the period after $[1, n]$, where 0 is the publication date. The difference between the post and pre-publication date values is displayed in the fifth column. Columns 6 and 7 test the equality of the post and pre- publication averages. The former shows the $p$-Value under the alternative hypothesis, $H_a : \triangle\sigma < 0$. The latter shows the $p$-Value under the alternative hypothesis, $H_a : \triangle\sigma > 0$. Panel (2) displays the cross-sectional average beta over different time periods around the date in which the first rumor concerning the leader's health was published. Beta is computed using daily returns in windows of 60, 100 and 200 trading days for both the period before the publication $[-n, -1]$ and the period afterwards $[1, n]$, where 0 is the publication date. In order to account for non-synchronous trading, the market model parameters are computed using the method proposed by Scholes and Williams (1977). The difference between the post and pre-publication date values is displayed in the fifth column. Columns 6 and 7 test the equality of the post and pre-publication betas. The former shows the $p$-Value under the alternative hypothesis, $H_a : \triangle\beta < 0$. The latter shows the $p$-Value under the alternative hypothesis, $H_a : \triangle\beta > 0$.

# 7 Conclusion

Recent popular literature and scholarly writings emphasize the importance of national leaders on stock market performance around the globe. This paper uses exogenously timed leader transitions to identify the causal effect that leaders have in stock markets.

We find that the effect of leadership transitions across countries depends on the nature of their exit. Surprising deaths due to accidents, for instance, are not associated to systematic changes in cumulative abnormal returns or structural shifts in volatility. Exits due to the worsening of long-standing illness, on the other hand, are associated to a positive cumulative abnormal return across countries. Our results suggest that this positive impact is due to a rebound effect from the negative impact that initial news about these leader's health problems had on the markets.

These results contribute to the growing literature on the importance of leaders shaping economic outcomes. In particular, the results on this paper are consistent with the idea that investors perceive a leader's illness as an impediment for good governance. Our results also suggest that stock markets (and countries with relatively strong institutional arrangements to sustain them) cope, on average, better with the tragedy of suddenly losing healthy national leaders.

An important extension to this analysis would be to gather data on stock prices of individual companies across countries. This approach could shed light on how political connectedness of the leader affects particular firms and industries. In addition, it would permit an analysis of resource allocation and overall performance of the market. It would also be potentially interesting to explore additional leader and country characteristics that may mediate the effect of a leader's exit on market performance. Finally, it would be interesting to explore the details and strategic interactions within a leader's inner circle of a government when the leader is not performing governing activities in full capacity. Sometimes the leader or his close circle do not disclose the full severity of the leader's ailment to avoid relinquishing power. The main issue would be to gather comparable data on the composition of the leader's inner circle.

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# 8 Appendix

## 8.1 Comparison to Besley et al. 2011

As a validation procedure, we compare our sample of unexpected exits with the one used by Besley et al. (2011). They use a total of 183 political leaders who were in office between 1875 and 2004. From this list, 174 leaders are also included in the initial sample we constructed from Archigos 3.0 (before trying to pair each entry with stock market data). Table 15 presents the remaining 9 cases and the reason why they are not included in our sample. Out of these 9 cases, 6 are not included in our version of Archigos, one is labeled as a regular exit in Archigos, one is recorded in Archigos under a different name, and another one corresponds to an exit influenced by a third party.

Table 15: Missing Leaders from Besley's List

| Name | Country | Reason |
|---|---|---|
| Rosie Douglas | Dominica | No entries from this country in Archigos 3.0 |
| Juhu K. Paasikivi | Finland | Regular exit according to Archigos 3.0 |
| Herbert A. Blaize | Grenada | No entries from this country in Archigos 3.0 |
| Ntsu Mokhehle | Lesotho | Exit influenced by third party according to Archigos 3.0 |
| Amata Kabua | Marshall Islands | No entries from this country in Archigos 3.0 |
| Richard John Seddon | New Zealand | Not included in Archigos 3.0 |
| Ibn Saud | Saudi Arabia | Name should be corrected to Aziz according to Archigos 3.0 |
| Mehmed V Reshad | Ottoman Empire | No entries from this country in Archigos 3.0 |
| Ionatana Ionatana | Tuvalu | No entries from this country in Archigos 3.0 |

Notes: Observations that were included in the sample used by Besley et al. (2011) but were not included in our sample due to the reason displayed in the third column.

## 8.2 Parameter Estimation of the Market Model for Abnormal Returns

We estimate the parameters of the model, $\hat{\alpha}_j^*$ and $\hat{\beta}_j^*$, using the method proposed by Scholes and Williams (1977) to account for non-synchronous trading. $\hat{\beta}_j^*$ is computed as follows:

$$\hat{\beta}_j^* = \frac{\hat{\beta}_j^- + \hat{\beta}_j + \hat{\beta}_j^+}{1 + 2\hat{\rho}_w},$$

where $\hat{\beta}_j^-$, $\hat{\beta}_j$ and $\hat{\beta}_j^+$ are OLS estimates from the regression of $R_{w,j,t-1}$, $R_{w,j,t}$ and $R_{w,j,t+1}$ on $R_{j,t}$ respectively, and $\hat{\rho}_w$ corresponds to the estimated first-order autocorrelation coefficient of $R_{w,j,t}$. We used an estimation window for these parameters of 200 trading days, from day -250 to day -50 before each leader's exit.

The parameter $\hat{\alpha}_j^*$ is computed as follows:

$$\hat{\alpha}_j^* = \overline{R_{j,Est}} - \hat{\beta}_j^* \cdot \overline{R_{w,j,Est}},$$

where $\overline{R_{j,Est}}$ and $\overline{R_{w,j,Est}}$ are the mean return of the country and world index, associated to the exit of leader $j$ over the estimation window, respectively.

## 8.3 Test Statistic for CAAR

We follow Patell (1976) to compute the test statistic used to test if the null hypothesis that the CAAR is zero is correct.

The variance of the abnormal returns in the event window is estimated by their variance in the estimation window. We use the following unbiased estimate:

$$s_{A_j}^2 = \frac{\sum_{k=E_1}^{E_2} AR_{j,k}^2}{M_j - 2}. \tag{3}$$

Where $E_1$ and $E_2$ are the start and end of the estimation window, respectively, and $M_j$ is the number of trading days on it. We subtract 2 from $M_j$ due to the number of degrees of freedom of the market model. The adjusted variance or adjusted standard error is:

$$s^2_{A_{j,t}} = s^2_{A_j} \cdot \left[ 1 + \frac{1}{M_j} + \frac{\left(R_{w,j,t} - \overline{R_{w,j,Est}}\right)^2}{\sum\limits_{k=E_1}^{E_2} \left(R_{w,j,k} - \overline{R_{w,j,Est}}\right)^2} \right] \tag{4}$$

Using the former expression, we can compute the standardized prediction error or standardized abnormal return ($SAR$):

$$SAR_{j,t} = \frac{AR_{j,t}}{s_{A_{j,t}}} \tag{5}$$

Under the null, $SAR_{j,t}$ follows a Student's $t$ distribution with $M_j - 2$ degrees of freedom.

We now need to accumulate the $SARs$ over the event window to obtain the cumulative standardized abnormal return ($CSAR$).

$$CSAR^j_{T_1,T_2} = \sum_{t=T_1}^{T_2} SAR_{j,t} \tag{6}$$

The expected value of this new variable is zero and its variance, $Q^j_{T_1,T_2}$, is equal to the sum of the variances of each $SAR_{j,t}$.

$$Q^j_{T_1,T_2} = \sum_{t=T_1}^{T_2} \frac{M_j - 2}{M_j - 4} = (T_2 - T_1 + 1) \cdot \frac{M_j - 2}{M_j - 4} \tag{7}$$

We then standardize $CSAR$ using its standard deviation and obtain a new statistic, $Z^j_{T_1,T_2}$, that distributes as N(0,1) under the null. $Z^j_{T_1,T_2}$ is defined as follows:

$$Z^j_{T_1,T_2} = \frac{1}{\sqrt{Q^j_{T_1,T_2}}} \cdot \sum_{t=T_1}^{T_2} SAR_{j,t} \tag{8}$$

Finally, we accumulate the $Z^j_{T_1,T_2}$ statistic over the number of exits and standardize the result in order to obtain $Z_{T_1,T_2}$, which allows us to tests if $CAAR_{T_1,T_2} = 0$.

$$Z_{T_1,T_2} = \frac{1}{\sqrt{N}} \cdot \sum_{j=1}^{N} Z^j_{T_1,T_2} \tag{9}$$

Under regular assumptions, $Z_{T_1,T_2}$ follows a Standard Normal distribution under the null.

## 8.4 Bootstrapping $p$-Value for CAAR

For any given subsample (e.g., unsurprising or surprising exits) and window size we have $N$ independent observations of CARs ($CAR_1$, $CAR_2$, ... , $CAR_N$) where $N$ is the number of exits in the subsample. These observed values follow an unknown probability distribution, of which we are interested in determining the mean. We do this by bootstrapping, i.e., we randomly draw multiple subsets with replacement and average them. We compute the $p$-value by counting how many of these values are smaller than or equal to 0.

Specifically, the procedure used consists in resampling the CARs 10,000 times and in each iteration $i$, obtaining a bootstrapped $CAAR_i$. To determine if we can reject the null hypothesis, we calculate the $p$-Value for a one-sided test by dividing the number of bootstrapped values that are smaller than or equal to 0 (or greater than or equal to 0 when studying the effect of rumors) by the total number of iterations. In order to remove the effect of outliers, we also take a second approach. Before resampling we first winsorize the set of CARs. Due to the small number of entries in some of our subsamples we do this at the $10^{th}$ and $90^{th}$ percentiles, since at lower levels no values would be winsored. After this step the procedure is identical to the one described above.

## 8.5 Monte Carlo Simulations for $K$

Recall that the first step to compute $K$ for leader $j$, is to obtain the percentile rank of his or her CAR (i.e., the CAR associated to leader $j$ around his or her date of exit) with respect to auxiliary CARs for neighboring windows. By using Monte Carlo simulation we can compute multiple $K$'s associated to leader $j$ by resampling the auxiliary CARs from which the percentile rank is computed. Using this method, with 10,000 iterations, we build empirical distributions of the $K$ statistic, and used them to test its significance.

## 8.6 What Drives Stock Markets around Random Transitions?

The well-known dividend discount model, developed by Gordon and Shapiro (1956), provides a simple benchmark to understand what may be driving stock markets around unexpected exits. In this model, asset prices are given by:

$$P_0 = \sum_{t=1}^{\infty} \frac{Div_t}{(1 + r_E)^t}$$

where $Div_t$ is the expected dividend payment of the asset in period $t$ and $r_E$ is the expected equity cost of capital. Therefore, the asset's price today, $P_0$, is equal to all future expected dividends discounted at the corresponding cost of capital. The equity cost of capital embeds the associated risk of the future dividend and is usually computed using the CAPM model as follows:

$$r_E = r_f + \beta_E \cdot (r_M - r_f)$$

where $r_f$ is the expected risk free rate, $r_M - r_f$ is the expected market risk premium, and $\beta_E$ is the equity beta that measures the asset's systematic risk.

Accordingly, a positive price jump on an asset should entail an increase on its expected dividends (cash-flows), or a decrease on its expected cost of capital, or both. If the risk free rate and the market premium remain unchanged, a change on the cost of capital would be proportional to a change on beta. Moreover, in a well-diversified portfolio, such as a market index, idiosyncratic risk should be fully diversified and a change on volatility would also lead to a change on beta, and therefore, on the cost of capital.

Since we do not find any significant change in volatility or beta, that could be changing the equity cost of capital, our evidence suggests the change in prices is due mainly to an increase (or decrease in the case of rumors) on future expected cash-flows.