The Power of the Street:

Evidence from Egypt's Arab Spring*

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Abstract

Unprecedented street protests brought down Mubarak's government and ushered in an era of competition between three rival political groups in Egypt. Using daily variation in the number of protesters, we document that more intense protests are associated with lower stock market valuations for firms connected to the group currently in power relative to non-connected firms, but have no impact on the relative valuations of firms connected to rival groups. These results suggest that street protests serve as a partial check on political rent-seeking. General discontent expressed on Twitter predicts protests but has no direct effect on valuations.

JEL classification: E02, G12, G3, O11, O43, O53

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1 Introduction

From the Arab Spring to the latest uprising against Victor Yanukovic's government in Ukraine, corruption and favoritism have motivated people to pour into the streets to protest against the economic and political arrangements benefiting connected individuals and firms. Such protests have sometimes been successful in unseating unpopular rulers, as illustrated by the recent events in Tunisia, Egypt, Libya, and Ukraine. But are they effective in limiting the corruption and favoritism that set them off in the first place? In other words, can protests in countries with weak institutions serve as a partial check on rent-seeking activity?

This paper strives to shed light on this question by studying Egypt's Arab Spring. On February 11, 2011, Hosni Mubarak, Egypt's president and *de facto* dictator, was forced to resign in the face of large protests in the main square of Cairo, Tahrir Square. Rampant corruption, benefiting mainly a narrow group centered around Mubarak's National Democratic Party (NDP), and repression, which excluded vast segments of the population from political participation, were major triggers of the protests. Mubarak's fall was followed by military rule until June 2012, when Mohammed Mursi, an Islamist, was elected president. Mursi's presidency in turn was followed by a second phase of military rule starting in July 2013. Throughout these four phases of Egypt's Arab Spring, politically connected firms (those connected to the NDP, the military, and the Islamists) have seen their fortunes ebb and flow, offering a window to study the real-time effects of street protests against a changing cast of ruling political elites.

Our primary approach for discerning the impact of street protests is to study their influence on the stock market valuations of different types of firms. This methodology estimates the value of political connections from changes in the relative stock market valuations of politically connected firms. It is particularly useful when there is a well-defined set of connected firms, as is the case in Egypt, and when direct measures of corruption and the shifting rent-seeking abilities of different groups of firms are unavailable (as they often are).

As a prelude to our main results, we show a series of event studies, which both illustrate the major political events of Egypt's Arab Spring and confirm that stock market returns in Egypt contain information about the changing value of political connections resulting from these events. For example, we find that in the nine trading days following Mubarak's fall, the value of firms connected to the NDP fell significantly (by about 13%) relative to the value of non-connected firms, indicating a perception of major rent shifts away from these firms in the Egyptian Stock Exchange. Since NDP-connected firms were longstanding beneficiaries of state-sanctioned monopolies (as we document further below), this result is quite plausible. We also show that subsequent key events impacting the power of the military and the Islamists are reflected in the stock market returns of firms connected to these groups.

Having established that political connections are reflected in the Egyptian stock market, our main results focus on the direct effect of street protests on the returns of politically connected firms. Using information from Egyptian and international print and online media, we construct daily estimates of the number of protesters in Tahrir Square and analyze the effect of these protests on the returns of firms connected to the group then in power. Our specifications estimate the differential changes in the stock market values of different types of connected firms relative to non-connected firms as a function of the size of the protests. They show a robust and quantitatively large impact of larger protests on the returns of firms connected to the incumbent group. For example, a turnout of 500,000 protesters in Tahrir Square lowers the market valuation of firms connected to the incumbent group by 0.8% relative to non-connected firms. Interestingly, there is no offsetting gain in the value of "rival" (non-incumbent) connected groups, a finding that will be important for our interpretation below. We also verify that the association between street protests and the stock market valuations of politically connected firms is not just a reflection of spikes in protests during some of the key events already mentioned above. In other words, even during periods when protests did not lead to changes in governments or institutions, protest activity is strongly associated with swings in the relative stock market valuations of (incumbent) connected firms.

We further use data from the universe of tweets by Egyptian Twitter users during this period to shed light on several interrelated questions. First, we document that activity on Twitter predicts protests in Tahrir Square, suggesting that social media has helped coordinate street mobilizations. Second, we also find that this social media activity has no direct effect on stock market valuations with or without simultaneously conditioning on street protests. This finding is interesting in part because it suggests that, despite the considerable emphasis on the role of social media in the Arab Spring, street protests may have still had a special role, and the same discontent expressed via social media may not have the same impact as popular mobilization. This might be because street protests are more visible (making the discontent "common knowledge") and/or because they involve a greater degree of coordination among participants.

We consider several possible interpretations of these findings. The first is that the association between street protests and differential fluctuation in the stock market valuation of connected firms reflects not the value of political connections but the heterogeneous responses of firms with different characteristics to macroeconomic shocks. We believe that this is unlikely to be the case since we control for various firm-level characteristics and for the sectors in which each firm operates; we estimate stock market effects immediately after protests, and not before; and we also find changes in profitability and board composition consistent with a shift of rents away from NDP-connected firms.

A second interpretation is that street protests do affect the value of political connections, but merely reallocate rents between different politically powerful groups as different regimes rise and fall—without any influence on the overall extent rents captured by connected firms. None of our specifications, however, show evidence of offsetting positive impacts of street protests on the stock market valuation of firms connected to the other two rival groups (again relative to non-connected firms). Even though rents might be reallocated to non-listed firms or to newly-emerging connected firms not yet listed, under most plausible scenarios of rent reallocation, existing listed, large firms connected to rival groups should be some of the main beneficiaries. The fact that we find no evidence of such offsetting shifts leads us to believe that street protests have farther-reaching effects on rents than a pure reallocation.

A third possibility is that street protests not only affect the identity of the group in power, but also limit the overall ability of connected firms to benefit from their political connections by changing the future distribution of political power in society. This might be because protests increase the likelihood of future major changes in formal, *de jure* institutions, affecting the ability of the politically powerful to extract rents (e.g., a constitutional change in favor of better protection of property rights or the election of a less corrupt regime). Relatedly, protests may curtail the ability of elites to extract rents by mobilizing or solving the collective action problem of certain groups, thus facing the politically powerful with the threat of future uprisings. If so, spikes in protests can be a source of *de facto* power in a society (even if *de jure* institutions remain unresponsive to popular demands), and may act as a constraint on the ability of connected firms to siphon off rents. This latter interpretation is made somewhat more plausible by the results in the previous literature that protests during various critical periods have an autonomous impact both on future protests and on certain economic and political outcomes (Aidt and Franck (2015), Collins and Margo (2007), Madestam et al. (2013); see our discussion below), and by our finding on the interplay between social media activity and protests.[1]

Our reading of the evidence is most consistent with this third possibility, but does not enable us to distinguish the relative roles of the *de jure* and *de facto* channels. The fact that our main results hold even when we restrict attention to periods when there was no change in political institutions or government and when such a change did not appear likely to be forthcoming anytime soon, suggests that the *de facto* channel is at least part of the story.

Our methodology builds on the literature on political connections, which uses stock market returns as a measure of the (changing) value of politically connected firms (Roberts, 1990). The seminal study in economics is Fisman (2001), who exploited rumors about Indonesian President Suharto's health and found that the value of connections accounted for 23% of firms' value in the Indonesian stock market during the mid-1990s. Similar results are found for Malaysia (Johnson and Mitton, 2003), Pakistan (Khwaja and Mian, 2005), and Weimar Germany (Ferguson and Voth, 2008).[2] Recent independent work by Chekir and Diwan (2015) uses the fall of Mubarak to estimate the value of political connections. We differ from this paper and the rest of this literature primarily because of our focus on street protests as the source of change of *de facto* power and our investigation of whether their effects are due to rent reallocation or constraints on rent generation.[3]

The second literature we are building on studies the effect of protests and social unrest on political change. Acemoglu and Robinson (2000, 2006) emphasize the effect of protests (and the threat of revolution or uprisings) on changes in political regimes. In particular, they suggest that protests which temporarily shift the *de facto* distribution of political power in society may force a change in political institutions so

[1] There are several caveats that need to be borne in mind. First, despite our independent evidence on profitability and board composition, most of our results rely on stock market participants' perception of future rents. Second, some of the firms we classify as non-connected may nevertheless have political connections. Finally, given the very specific circumstances in Egypt during this time period, it is difficult to draw inferences about the general impact of street protests on political and economic outcomes in other institutional and historical settings.

[2] See also Dinç (2005), Faccio (2006), Faccio et al. (2006), Leuz and Oberholzer-Gee (2006), Snowberg et al. (2007), Bunkanwanicha and Wiwattanakantang (2009), Dube et al. (2011), Akey (2015), and Acemoglu et al. (2016) for various other applications of this methodology.

[3] Another strand of the literature has investigated the mechanism by which politically connected firms extract rents. See, for example, Heydemann (2004), Henry and Springborg (2010), Roll (2010), Rijkers et al. (2014). Particularly relevant in this context is the work by Diwan et al. (2015) on Egypt.

as to alter the future distribution of *de jure* political power. Several empirical and historical papers have found evidence consistent with this idea (e.g., Aidt and Jensen (2013), Aidt and Franck (2013)), and some others have modeled the decision to take part in protests and the implications of these endogenous protests on political equilibria (e.g., Kuran (1989, 1991), Lohmann (1994), Fearon (2011), Kricheli et al. (2010), and Bidner and Francois (2013)). Another branch of the literature (e.g., Collins and Margo (2007), Madestam et al. (2013), Chaney (2013)) is more closely related to our interpretation as it shows that short-run, random factors that prevent or facilitate protests have a durable impact on political organization and social and economic outcomes.[4] To the best of our knowledge, this literature has not investigated the role of street protests on constraining or redistributing economic rents from favoritism and corruption.[5]

A final literature we relate to investigates the role of social media in political events (e.g., for a theoretical analysis, see Edmond (2013), and for empirical work, see Adamic and Glance (2005), Halberstam and Knight (2014), Weber et al. (2013) in the context of Egypt, and Enikolopov et al. (2016) in the context of Russia). Our paper contributes to this literature by showing the impact of social media activity on street protests and also by clarifying how this activity might or might not influence the extent and distribution of rents in the economy.[6]

2 Data

Our dataset comprises 177 firms that were listed on the Egyptian stock exchange on January 1, 2011. We obtain daily closing prices for each of these firms between January 1, 2005, and July 31, 2013, from Zawya, a financial data provider specializing in the Middle East. The same vendor also provides accounting data and stock return indices. We use these data to construct daily stock returns for each of the firms in our sample, as well as quarterly measures of the size (total assets) and leverage (total debt over total assets) of each firm.

[4] We are also related to, but sharply differ from, another subbranch emphasizing the economic costs of political instability (e.g., Alesina and Perotti (1996), Alesina et al. (1996), Svensson (1998), Overland et al. (2005), and Haber et al. (2004)). In our setting, certain types of protests under weak institutions (as those in Egypt) may serve as a partial check on rent-seeking activity.

[5] Campante and Chor (2012), Chaney (2012), Gilli (2012), and Kent and Phan (2014) discuss the origins of the Arab Spring.

[6] A piece of evidence from a completely different context that is consistent with our finding that general discontent voiced on social media has limited political effects comes from the work of King et al. (2013) who show that Chinese censors permit expression of general discontent on social media but aim to silence any attempt at mobilization for collective action.

As standard controls, we estimate an Egyptian- and a world-market beta for each firm by regressing the daily stock returns of each firm during the 2010 calendar year on the returns on the MSCI-Egypt and MSCI-world indices, respectively.

In addition, we use information from the Global Data on Events, Location, and Tone (GDELT) dataset to construct a measure of the sensitivity of a firm's stock return to general unrest in the country. GDELT uses English-language news sources to compile a list of approximately 250 million political events that occurred across the world from 1979 to the present. For each event, GDELT uses simple grammatical rules to identify an action taken by an actor in a given location upon another actor (in essence, subject, verb, object). We use this dataset to obtain a list of strikes, boycotts, riots, and instances of ethnic clashes between Muslims and Christians that occurred between January 1, 2005, and Dec 31, 2010. We then regress the stock returns for each firm on a dummy variable that is 1 on the two trading days following one of the events on our list, and refer to the slope coefficient of this regression as "unrest beta," β_i^{Unrest} (see Appendix A.1 for details).

Connected Firms. Firms listed on the Egyptian stock exchange publish quarterly reports disclosing the names of their board members and principal shareholders (individuals or entities that hold more than 5% of the firm's equity). We base our classification on the set of reports describing the situation as of January 1, 2011, immediately before the onset of Egypt's Arab Spring.[7]

We classify a firm as connected to the NDP if the name of at least one of the firm's major shareholders or board members appears on a list of 6,000 prominent NDP members posted online by activists in the aftermath of the fall of Mubarak's regime. This list was created as part of a campaign, "Emsek Felool" ("to catch remnants" of the old regime), to publicly identify the cronies of the old regime.[8] The list gives the name, rank within the NDP, and official function of each prominent NDP member by Egyptian governorate. The types of functions it lists include members of parliament, aldermen, and local and party council members. Our algorithm matches 19 names in 22 firms. (See Appendix A.2 for details.)

In accordance with the Egyptian constitution, the Egyptian military's financial accounts are outside

[7] The first reports were filed for the second quarter of 2011, but they contain a section on the status of board members and shareholder structure for the previous quarter, thus also covering the relevant information for the first quarter of 2011.

[8] For a description of the "Emsek Felool" campaign, see articles published by The Guardian and The Wasthington Post on Nov 16, 2011. At the time of writing, the original list was no longer publicly available. It is available from the authors upon request.

the control of the civilian government (the “two tills” system). This system has historically allowed the Egyptian military to operate autonomously and build a largely opaque empire of economic activities outside of civilian control (Harb, 2003). We classify listed firms as connected to the Egyptian military if they are wholly or partially owned by the military “till.” We identify these firms by first selecting all state-owned holding companies, that is, government-owned entities that hold stock in listed firms, from the Zawya database. Although these holdings do not officially declare which of the two “tills” they are accountable to, we distinguish between military- and civilian-government-owned holdings by checking whether the principal officers, shareholders, or board members of the holding company (or any of its affiliated firms) are linked to the military. For this, we use a variety of sources (see Appendix A.2 for details). Using this procedure, we obtain a list of 12 military-controlled holding companies that own stakes in listed firms. We then classify a listed firm as connected to the Egyptian military if one of these 12 companies appears on the list of its principal shareholders, giving us 33 military-connected firms in total. Consistent with a strict division between military and civilian control, we find *no overlap* between NDP- and military-connected firms.

In addition to NDP- and military-connected firms, we also attempted to identify firms connected to the Muslim Brotherhood (MB) by collecting the names of prominent members from various sources and cross-referencing them with the names of principal owners and board members of listed firms. Despite committing significant resources to this effort, we identified only one connection to the MB. This negative finding may indicate that the MB did not manage to penetrate listed firms in the Mubarak era. An alternative explanation, which we find more plausible, is that those involved may have been more likely to go to great lengths to conceal any such connections, for the obvious reason that the MB was outlawed, and thus operated underground for most of its existence.[9] As a partial substitute for identifying links to the MB, we generate a dummy variable for firms that Zawya or MSCI classify as operating according to Islamic principles. Both data vendors maintain such classifications to enable Islamic investment. For example, MSCI’s criteria require that firms adhere to Islamic principles both in the conduct of their business (no investment in firms that derive more than 5% of their revenue from alcohol, tobacco, pork, weapons, gambling, etc.) and in their financing (no significant income from interest, etc.).[10] We refer to these firms as “Islamic” because they

[9]This is consistent with the fact that we were only able to compile a list of a few hundred names of publicly known Muslim Brothers, in contrast to the NDP, for which we have a list of 6,000 members.

[10]See MSCI’s website for details on this classification (http://www.msci.com/products/indexes/thematic/faith-

are likely to benefit relative to their competitors under an Islamist government. For ease of reference, we also sometimes refer to them as "connected" or with some abuse of English, "Islamic-connected." However, because there is some uncertainty about the degree to which these firms have operational political connections to the Islamist movement we present our main results both with and without the inclusion of this category. Of the 13 Islamic firms, five are also connected to the NDP, while the remaining eight are connected neither to the NDP nor to the military.

Panel A of Table 1 shows summary statistics for the three types of connected firms, where we refer to non-connected firms as those that fall into none of the three categories. The table presents means and standard deviations of firm characteristics as of January 1, 2011, before the beginning of Egypt's Arab Spring. The first panel gives statistics for all firms. The second and third panels show the same statistics for connected versus non-connected, as well as separately for NDP-, Military-, and Islamic-connected firms. On average, NDP-connected firms have assets of 2,436 million Egyptian pounds and are thus significantly larger than than the average military-connected firm (with assets of 240 million Egyptian pounds). NDP-connected firms also tend to have somewhat higher leverage (computed as total debt divided by total shareholder assets). Reassuring for our comparisons below is that all types of firms appear to have similar Egyptian, world-market, and unrest betas on average.

Appendix Table 1 shows the number of NDP-, military-, and Islamic-connected firms in each of the 16 sectors of the economy. Once again reassuringly, all types of firms have representation in a variety of sectors. For example, military-connected firms cluster in industrial manufacturing but are also active in the food and beverage and the health care sectors. Not surprisingly, Islamic firms are clustered in financial services, but are also active in manufacturing, telecom, and real estate. Throughout our analysis, we include sector fixed effects in our regressions.

The Number of Protesters in Tahrir Square. Our main specifications relate stock returns of firms connected to the incumbent regime to daily variation in the number of protesters in Tahrir Square. We construct this series using text analysis of 102 English-language newspapers published between January 2011 and July 2013 in Egypt and around the world. To this end, we downloaded all newspaper articles

based/islamic/) and https://www.zawya.com/cm/analytics/default.cfm?full for the equivalent definition used by Zawya.

containing the words "protesters"/"protestors" and "Tahrir" and "Egypt" from newspapers in the category "major world publications" of the Lexis Nexis Academic service and from all available English-language Egyptian news outlets (Al-Ahram Gate, Al-Ahram Weekly, Al-Akhbar English, and Daily News Egypt). We supplemented this pool of articles with the online content of Al-Masry Al-Youm, Al-Ahram English, and Copts United in order to ensure that the Egyptian press our analysis covers is broadly balanced between pro- and anti-regime news outlets.[11]

We then programmed an algorithm that isolates the number of protesters (usually a term such as "hundreds"or "tens of thousands") reported by each article and identifies the day for which the number is reported (e.g., an article published on Tuesday might report on events on the same day, the previous day, or even a day in the previous week). We then assigned a numerical value to each word used. Finally, we set the number of protesters equal to zero for all days on which fewer than three separate outlets report a protest, and use the median number of protesters across outlets for all other days. Appendix A.3 gives the details of this algorithm and a sample of our mapping between words and numbers. Using the same algorithm, we also constructed a daily time series of the number of protesters in Rabaa Square, which became the rallying point for pro-Islamist protesters in the later stages of Egypt's Arab Spring.

Figure 1 plots the resulting estimates for the number of protesters in Tahrir Square for each day through the end of July 2013. Panel B of Table 1 presents summary statistics on the number of protesters for each of the four phases of Egypt's Arab Spring, which we describe below. Appendix Figure 1 shows the share of total Tahrir protesters over the sample period by weekday. It shows that the largest protests tend to be on Fridays (32.55% of total protesters). Because protests frequently occur on days on which the Egyptian stock exchange is closed (typically Fridays and Saturdays), we assign the number of protesters turning out on non-trading days to the following trading day in all specifications that relate returns to protests.

Data from Social Media. In some of our specifications, we relate stock returns and the number of protesters in Tahrir Square to activity on social media. In particular, we use data from Twitter to construct a measure of mobilization for street protests, a measure of political support for the political opposition, and a measure of the cohesiveness of the opposition.

[11] The political leanings of these newspapers vary. Some of them are considered to be independent (e.g., Al-Masry Alyoum and Daily News Egypt) and others are considered loyal to the state (e.g., Al-Ahram and Al-Akhbar).

To construct these measures, we obtained a list of 318,477 Egyptian Twitter users who tweeted at least once between July 1, 2013, and September 17, 2013, from an Egyptian social media firm (25trends.me). Using the Twitter Application Programming Interface, we downloaded the entire history of tweets made by each of these users. Although Twitter limits the downloadable history of each user to the 3,200 most recent tweets, less than 20% of users exceed this limit, enabling our procedure to cover the period back to January 1, 2011, in the majority of cases. We end up with approximately 311 million tweets made by Egyptian users between January 1, 2011, and July 31, 2013.

As a simple measure for the degree of mobilization for street protests, we count the tweets that contain hashtags referring to Tahrir Square on each day. We refer to this measure as "Tahrir hashtags." As a robustness check, we also counted all tweets that contain the words "Tahrir" anywhere in the body of the tweet. This alternative measure delivers almost identical results. To mirror our empirical approach on street protests, we assign tweets made during non-trading days to the following trading day in all specifications that relate Tahrir hashtags to stock returns.

To gauge the political support for the opposition on any given day, we identified the Twitter accounts of all prominent opposition figures that appear on the Socialbakers list of prominent Twitter accounts in Egypt. (Our definition of the political opposition changes as groups move in and out of power. See Appendix A.4 for details.) We then downloaded all daily tweets by these opposition figures and counted the number of retweets of these tweets on any given day. That is, we counted the number of times the tweets of opposition leaders were shared or forwarded by other users and use this count as proxy for the level of support for the political opposition. As an alternative measure, we also counted the number of unique retweeters of opposition figures—this again yields almost identical results.

Finally, we used our Twitter data to construct a measure of the nature and cohesion of the political opposition on a given day, "opposition turnover rate," which we describe below. Appendix A.5 gives details on the construction of our Twitter-based variables. Panel B of Table 1 lists summary statistics.

3 Egypt's Arab Spring and Its Impact on Rents

In this section, we provide a brief historical overview of Egyptian politics, emphasizing the role of the three key power groups: the military, the NDP, and the Islamist movement. We then describe the events of the Arab Spring and utilize the standard event study approach to document their impact on the stock market valuations of firms connected to different power groups (relative to non-connected firms), which is useful both as a way of documenting the extent of rents in the Egyptian corporate sector and confirming that stock market valuations do contain information about the changing fortunes of firms with different types of connections.

3.1 Historical Background

Following Colonel Nasser's takeover of power in the aftermath of the 1952 coup by the "free officers"against King Farouk, Egypt has for all practical purposes been under one-party rule. Originally named Liberation Rally, this party was renamed the Arab Socialist Union when Nasser aligned Egypt with the Soviet Union. Following his death, another member of the free officers, Anwar Sadat, became president and re-organized this party into the, ostensibly centrist, NDP. Consistent with its frequent repositioning, the NDP never had a clear ideology aside from being modernist and anti-Islamist. Instead, it collected members of the secular elite, bureaucrats, and cronies of the regime. Although founded by the free officers, the NDP quickly grew into an independent center of power, possibly because the successive presidents nurtured it as a counterweight to the military. After Sadat's assassination in 1981 by a radical Islamist, Sadat's vice president and former Air Force officer, Hosni Mubarak, rose to head the NDP and Egypt. In the final years of Mubarak's rule, the NDP expanded its influence and prominent NDP members acquired vast fortunes. Hosni Mubarak's son and would-be successor, Gamal Mubarak, had his power base in the NDP.

Throughout this period, the military has kept great power and influence. In addition to its political clout, the Egyptian military built a vast economic empire in civilian industries, which, under the aforementioned two tills system, was broadly beyond government regulation and tax authority. Politically, the military has traditionally opposed the Islamists.

Egypt's Islamist movement has been the main political force opposing the ruling coalition of military and NDP. Its main social organization is the Muslim Brotherhood (MB) founded by Hassan al-Banna in 1928. Its ideology favors a literal interpretation of scriptures and advocates a return to an idealized Islamic society. Its traditional followers are the urbanized middle and lower classes. The MB and the majority of its offshoots have been outlawed almost continuously since 1948. Although the MB initially supported the coup against King Farouk, Nasser cracked down on the movement almost immediately after taking power. Although outlawed, the MB continued operating and building a vast network of charitable organizations and religious schools throughout this period. In the later years of Mubarak's rule, it gained a semi-official status and most of its leaders were released from prison. In the 2005 election, candidates affiliated with the Islamist movement gained around 20% of seats in the Egyptian parliament.

The interplay of these three centers of power, the NDP, the military and the Islamists, was disrupted in 2011, when a broad coalition of disenfranchised youths, urban middle classes, and poor took to the streets of Cairo. The Arab Spring of 2011 originally began with the Jasmine Revolution in Tunisia, ignited by public outrage over the suicide of a street vendor in December of 2010. By early 2011, Tunisian President Bin Ali had stepped down, but far from abating, the revolutionary fervor against the rule of privileged elites in Tunisia was getting stronger and soon spread to Egypt.

On January 25, 2011, thousands (5,000 according to our measure) of protesters congregated in Tahrir Square for the first public demonstration against the Mubarak regime. In a country in which all public demonstrations were illegal and duly crushed, this protest was a watershed event. Moreover, the protests were organized not by Islamists but by young, middle-class Egyptians. Following this event, Egypt's Arab Spring unfolds in four stages: (1) the fall of Mubarak, (2) the rule of the military, (3) the rule of the Islamist Mohammed Mursi, and (4) the recovery of power by the military.

3.2 The Arab Spring in Event Studies

We now use standard event study methodology to describe the impact of key political events during each of the four phases of Egypt's Arab Spring on the rents—or the perception of rents—captured by different types of connected firms.

Our empirical strategy studies changes in the cumulative returns on each firm's stock between the opening of trade on trading day n and the closing of trade on the end trading day m (where we count all trading days relative to January 25, 2011, the day of the first large protest in Tahrir Square). Cumulative returns for firm i are defined as $CR[n,m]_i = \sum_{t=n}^{m} R_{it}$, where R_{it} is the log return of firm i between its previous trading day and t (not all firms trade on each day in our sample). We relate changes in cumulative returns to the type of connection of the firm—NDP, military, Islamic—summarized by the vector N_i (i.e., N_i is a vector of three dummies for NDP-, military-, and Islamic-connected firms).

The empirical model we estimate can be written as

$$CR[n,m] = N_i'\gamma + X_i'\nu + \eta_s + \epsilon_i, \tag{1}$$

where X_i is a vector of controls, γ is a vector of coefficients, one attached to each one of the dummies in N_i, η_s denotes a full set of sector fixed effects, and ϵ_i is an error term. Because our sample includes non-connected firms, the vector of coefficients γ measures how the cumulative stock market returns of a group of connected firms have changed relative to the returns of non-connected firms. This strategy is valid if, absent the political events taking place during this window, no systematic differences would exist between the returns of the different types of connected firms and the non-connected firms. In other words, we require the standard identification assumption $Cov\left(N_i', \epsilon_i \mid X_i, \eta_s\right) = 0$.

The plausibility of this assumption depends on the controls we include in the vector X_i. In our baseline specification, these controls are, in addition to a constant term, the betas, β_i^{World}, β_i^{Egypt}, β_i^{Unrest} (as described above), a full set of (16) sector fixed effects, and controls for size and leverage. Our specification here is a slight deviation from the earlier event study literature in that, instead of constructing abnormal returns relative to an Egyptian Capital Asset Pricing Model, we include both the Egyptian and world market betas as controls on the right-hand side.[12] Several considerations motivate this choice. First, our specification allows for partial diversification between Egyptian and world markets, an important advantage in view of the fact that the Egyptian stock market is only a small part of the world market. Second, by separately including the betas for the world market and the Egyptian markets, as well as the unrest beta, this approach controls for omitted factors in a more flexible manner. Our inclusion of sectoral dummies and

[12] In some of our specifications, we follow the earlier literature and work with cumulative abnormal returns computed as $CAR[n,m]_i = \sum_{t=n}^{m} R_{it} - \left(\alpha_i - \beta_i^{Egypt} R_t^{Egypt}\right)$.

controls for size and leverage is motivated by the potential differential impacts of political unrest on firms that are in different sectors or have different characteristics or exposure to various risks.[13]

All standard errors we report throughout are robust to heteroscedasticity. In addition, because there might be other factors correlated across connected firms, we report adjusted standard errors and portfolio-based results that account for potential cross-firm correlation of residual returns in the appendix (Schipper and Thompson, 1983; Fama and French, 2000; Greenwood, 2005; Becker et al., 2013).[14] These robustness checks consistently show that residual returns are negatively correlated with the group of politically connected firms, such that adjusted standard errors tend to be narrower than unadjusted standard errors. To be conservative, we therefore report the wider (robust) standard errors in the main text.

As an alternative to the empirical model described above, we also report results from a synthetic matching estimator aimed at constructing a more informative control group for each connected firm. Following Abadie and Gardeazabal (2003), Abadie et al. (2010), and Acemoglu et al. (2016), we construct the control group separately for each connected firm as a convex combination of the subset of non-connected firms that minimizes the deviation of the pre-event behavior of the connected firm from the control group, where the pre-event window contains all trading days between January 1 and December 23, 2010. Intuitively, in contrast to our OLS regression results, which compare firms that are similar in terms of the covariates, this approach compares firms that are similar in terms of the behavior of their pre-event stock market returns. Appendix B.2 gives details on the construction of this estimator

[13] We interpret the vector γ as the effect of the event in question on market participants' expectation of the net present value of economic rents accruing to the three types of connected firms relative to the value of non-connected firms. This interpretation is subject to a number of caveats. First, any change in the value of non-connected firms will lead to a simultaneous change in all of the components of the vector γ. Second, a negative estimate of a component of γ may also reflect some systematic expected discrimination against these firms. Third, any macroeconomic changes differentially impacting some sectors or types of firms could manifest as positive or negative estimates of the components of γ. Fourth, rents may be accruing to powerful minority shareholders, and their ability to capture such rents might vary over time and affect our estimates of γ (Karolyi, 2015).

We do not find the first two concerns to be major in the Egyptian context. We will investigate the third issue in detail, and can note here that the robustness of our results to sectoral controls indicates that they are not driven by the expectation that different governments will pursue policies favoring different sectors (as in Knight (2006)). Concerning the fourth, we believe that it would operate in the opposite direction to our results; for instance, if, after the fall of Mubarak, NDP-connected minority shareholders became weaker and were no longer able to capture rents at the expense of other shareholders, we should see an *increase* (rather than a decrease) in the stock market returns of NDP-connected firms relative to non-connected firms.

[14] To perform this, we run specification (1) for each trading day in the year prior to Egypt's Arab Spring (the 2010 calendar year) and use the residuals from this estimation to calculate the cross-correlation matrix of residuals. We then use this estimated cross-correlation matrix to adjust our standard errors. See Appendix B.1 for details.

3.3 Mubarak's Fall

After January 25, 2011, the protests against Mubarak's regime quickly gained momentum. On Friday January 28, about 50,000 protesters turned out and large daily demonstrations followed in Tahrir Square. The Egyptian stock exchange, located in an adjacent side street, did not re-open the following Sunday and remained closed as the protests continued to grow. More than 500,000 protesters filled the square on February 1, 8, and 11, according to our estimates. On the evening of February 11, the vice president, Omar Suleiman, publicly announced Mubarak's resignation, and the hand-over of power to the military leadership. The following weeks were a period of instability. The police had all but disappeared from the streets, and looting, violence, and protests continued. By March 23, a measure of order had been restored and the Egyptian stock exchange resumed regular trading.

Table 2 analyzes this period using our event study methodology. The event window [0,8] ranges from January 25 until the end of the first week of trading after the re-opening of the exchange on March 30. Column 1 shows our most parsimonious specification which, in addition to the indicators for NDP-, military-, and Islamic-connected firms, includes sector fixed effects. During the event window, there was a large (approximately 20%) fall in the market overall. More importantly, we see a negative and marginally significant effect on NDP-connected firms (-0.086, s.e.=0.049) and a positive and again marginally significant effect on military-connected firms (0.048, s.e.=0.028), suggesting a sizable decline in the value of NDP-connected firms relative to non-connected firms and a non-trivial increase in the value of military-connected firms at the same time.

Column 2 shows our baseline specification in which we control for size and leverage as well as the world-market, Egyptian-market, and unrest betas. We now find a larger effect on NDP-connected firms (-0.131, se.e.=0.049) that is statistically significant at the 5% level.[15] The effect on military-connected firms declines in magnitude and is no longer statistically distinguishable from zero. This result implies that the loss of connections to the Mubarak regime reduced the market valuation of NDP-connected firms by 13.1 percentage points over the 65 days (9 trading days) after the first large demonstration. In monetary terms, this loss is equivalent to $2.8bn or about 4.3% of the market capitalization of all Egyptian firms on January 1, 2011.[16]

[15]The results are very similar if we include higher-order controls. For example, including quartics in size and leverage leaves the coefficient on NDP-connected firms essentially unchanged (-0.121, s.e.=0.045).

[16]The size of this effect is comparable to other estimates in the literature. For example, Johnson and Mitton (2003) find an

Appendix Table 2 and Appendix Figure 2 show the same specification for alternative event windows, with similar results.

The remaining columns of Table 2 document the robustness of our baseline specification in column 2. In column 3, we drop the sector fixed effects and show that the same pattern is present even without these controls. In column 4, we adjust standard errors for the cross-correlation of error terms estimated in 2010 data, with very similar results and somewhat smaller standard errors, reflecting the (aforementioned) fact that the residual correlation between connected firms is negative. In column 5, we weight each firm with the log number of transactions in its stock to account for the different volumes of trade across stocks. The results are again very similar to those in our baseline specification in column 2.

Column 6 reports the estimates from our synthetic matching procedure. The effect on NDP-connected firms is again negative and somewhat larger (-0.200). We follow the standard procedure of constructing confidence intervals by randomly drawing 500 placebo NDP-connected groups from the non-connected firms and compute confidence intervals at each level of significance so that exactly the requisite fraction of estimates are located outside the confidence interval (see Appendix B.2 for details). The resulting confidence interval shows that the differential impact on NDP-connected firms is significant at 1%. The matching estimates also show a large and significantly negative effect on Islamic-connected firms (though this may partially result from the fact that five Islamic-connected firms are also connected to the NDP and our matching procedure does not control for dual connections).

In column 7, we use cumulative abnormal returns as dependent variable. The results are once again similar to our baseline specification.

As a falsification exercise, we repeat our estimation for the most major political events that took place in Egypt during the 2010 calendar year.[17] Because these events created instability and surprise for the markets but were never meant to displace the existing regime and/or limit its cronyism, investigating whether they have similar effects on connected firms is particularly informative. We should find similar results during these placebo events if, despite our controls and other strategies, the differential effects of Mubarak's fall

effect amounting to 6.3% of market capitalization over 13 months. Ferguson and Voth (2008) find an effect amounting to 5.8% of market capitalization over 60 days.

[17] These are the Nag Hammadi massacre, a strike for higher minimum wages, the extension of the state of emergency by parliament, the closure of four satellite TV channels, the beginning of unrest in Tunisia, and Bin Ali's ight from Tunisia.

(and other similar events we study below) on connected firms were driven by the differential sensitivities of these firms to macroeconomic shocks. If, on the other hand, the patterns documented here reflected the reduced prospects for the capture of rents by connected firms, we should not find such differential effects. The results, shown in Appendix Table 3, are reassuring in this respect as they show no significant changes in the relative stock market valuations of the three types of connected firms during any of the events listed.

Figure 2 shows the results of an additional falsification exercise in which we look at differential returns for NDP-connected firms in seven consecutive event windows of equal length prior to January 25, 2011. The left panel uses OLS, while the right panel uses our synthetic matching estimator. Both show that the coefficients on the dummy variable for NDP-connected firms (the dots in the figure) are indistinguishable from zero in all seven pre-event windows, contrasting with the large and statistically significant drop following Mubarak's fall.[18]

Overall, we believe the most plausible interpretation of these results is that Mubarak's fall triggered a change in the market's expectations of the rents that the NDP-connected firms would be able to capture in the future. Intriguingly, we also find some limited evidence of a positive impact on the market's perceptions of rents of military-connected firms, suggesting that there might have been some amount of expected rent reallocation across different power groups during this period. However, we will see that there is no similar pattern of positive effects on rival groups during later phases.

Because the collapse of Mubarak's regime was a major institutional change for Egypt, these results may reflect the expected consequences from this and other anticipated future *de jure* institutional changes, or the direct effects of changes in *de facto* power emanating from street protests on the rents of connected firms. We will next see that during other key events there continues to be a negative impact on firms connected to groups that lose power, even though there are no discernible changes in *de jure* political institutions but only changes in *de facto* power.

[18]In addition, Appendix Figure 3 shows the distribution of t-statistics on the NDP-, military-, and Islamic-connected dummies when we run our baseline specification on each trading day in the 2010 calendar year. The rate of false positives or negatives is close to 5% for the coefficients on each of the three dummy variables, suggesting that our baseline specification does not show a tendency to over-reject the null of no differential effects during the previous year.

3.4 Later Phases

The first phase of Egypt's Arab Spring ended on April 16, 2011, when an administrative court dissolved the NDP on charges of corruption and seized its assets. Panel A of Table 3 shows the differential returns for NDP-, military-, and Islamic-connected firms during key events of the second phase under military rule. The first key event is a major military crackdown against protesters beginning on July 31, 2011. During this period, the Supreme Council of the Armed Forces arrested key activists, and attempted repeatedly to forcibly clear Tahrir Square from the protesters who continued to demand elections and democratic reforms. These events ended on September 8, when the square was finally cleared, and soldiers demolished the encampments. Following a period of calm, protesters re-took Tahrir Square on November 17-20 (which constitutes our second event). The demonstrations continued thereafter, pressuring the military finally to allow presidential elections to take place, with the results of the first round announced on May 28 and the results of the runoff election announced on June 24 (corresponding to our third and fourth events). The Islamist Mohammed Mursi narrowly won this runoff against the former general Ahmed Shafiq with 51.7% of the vote.

A struggle for influence with the Supreme Council of Armed Forces dominated the first two months of Mursi's presidency. This struggle culminated with Mursi's sacking of Mohammed Tantawi (the Commander-in-Chief) and the four highest-ranking generals on August 12, 2012 (the fifth key event). On December 23, a new constitution promoting political Islam but also granting expanded powers to the military passed in a referendum in spite of a boycott by the secular opposition (our sixth event). From this point onward, Mursi became increasingly unpopular, with pro- and anti-Islamist demonstrations alternating in Tahrir square on different days. A new broad-based opposition movement, *tamarood* ("rebel"), first collected millions of signatures against his rule and then mobilized for street protests beginning on June 30, 2013. As millions poured into the streets protesting Mursi's rule, a smaller number of his supporters (up to 50,000 according to our measure) camped out in Rabaa Square. On July 4, a military coup removed Mursi from power (our seventh and final event).

The results of this series of event studies in Table 3 document a pattern broadly consistent with the view that political connections to the NDP, the military, and Islamists are reflected in stock prices. For example, after the military crackdown, military-connected firms gain 8% in value (coefficient=0.080, s.e.= 0.044), whereas they lose 2.4% when protesters re-take Tahrir Square. We see no differential returns for any group of connected firms right after the first round of the presidential elections, which may not be too surprising given that the voting outcome in this round did not strongly shift power towards any of the groups. After the second round, there is an increase in the relative value of all three groups, which might be consistent with many Egyptians' perception at this stage that the old regime and the Islamists had worked out a deal that would favor all three powerful groups and thus all connected firms (the fact that results were announced only after a week-long delay reinforced this suspicion). Following Mursi's sacking of the powerful generals, we see a positive effect on the Islamic-connected firms (coefficient=0.010, s.e.=0.006). We also find that the passage of Mursi's constitution has a negative effect on the value of NDP-connected firms, a finding consistent with the general belief at that time that this constitution was going to put an end to the role of the NDP in Egypt's political arena. Finally, after Mursi's fall, Islamic-connected firms experience a loss of value. These patterns appear to be quite robust to using alternative estimators and methods for adjusting standard errors, as we show in Appendix Tables 4-7.

We should note that the events with the most consistent results—the military crackdown, the re-taking of Tahrir Square by the protesters, and President Mursi's sacking of key generals—did not change *de jure* political power, political institutions, or the government in place. Instead, they were associated with changes in the balance of power and the *de facto* power of different groups, such as the protesters in Tahrir Square and the leading members of the MB. As such, these results are both a preview of our main findings on the effect of street protests and mobilization on (the perception of) future rents, which we present below, and an indication that this effect may have partly been due to shifts in *de facto* power that mattered in an environment with weak institutions.

As a parsimonious summary of the results in Tables 2 and 3, Table 4, estimates the average effect of all events on firms connected to the group then in power. We code a variable E_t that is zero on non-event days and takes the values -1, 0, or +1 on event days depending on whether the event was good, neutral or bad for the "incumbent" group then in power. We then interact this variable with two dummy variables. The first indicates firms connected to the group currently in power ("Incumbent"), the second indicates a connection to the other two rival groups ("Other Connected"). For example, the NDP is incumbent during the first phase of Egypt's Arab Spring and looses power during Mubarak's fall ($E_t = +1$). Similarly, the military is incumbent during all events shown in Panel A of Table 3 and gains power during the military crackdown ($E_t = -1$), and so on. We then run a regression of daily returns on the interaction of the event variable, E_t, with the incumbent and connected dummies. Column 1 of Table 4 shows our most parsimonious pooled specification which simply includes a full set of time and sector fixed effects as additional controls. We find a sizable and precisely estimated negative effect on the incumbent times event interaction (-0.340, s.e.=0.093), and a positive, small, and statistically insignificant coefficient for the non-incumbent times event interaction. Column 2 includes our set of controls (size, leverage, and the three betas for the Egyptian market, the world market, and unrest), fully interacted with time dummies, thus flexibly allowing for differential trends by these characteristics. Columns 3-6 include firm fixed effects, nonlinear interactions of our controls and time effects, interactions of the event variable and sector dummies, and full interactions of sector dummies and time effects. In all cases, the results are very similar and highly significant. Column 1 of Appendix Table 9 shows similar results using a portfolio-based estimation based on Schipper and Thompson (1983).

Throughout these variations, the tables shows a robust pattern: events reducing the power of the incumbent group translate into significant negative effects on the stock market returns of firms connected to this incumbent group (relative to non-connected firms), with no major impact on the stock market returns of non-incumbent groups.

3.5 Other Reactions and Outcomes for Connected Firms

If the political developments during Egypt's Arab Spring truly changed the ability of different types of firms to exploit their connections and capture rents, we would also expect to see firms exerting effort to acquire more politically valuable types of connections as well as changes in their profitability as the balance of political power shifts in society.

Though we do not have as detailed data on these outcomes, the available data, presented in Table 5, are consistent with these expectations. Panel A shows that one year after the beginning of military rule, we see fewer NDP members on the boards of the firms in our sample and more board members using military titles, indicating attempts by firms to disassociate themselves from the NDP and build military connections.

Similarly, we see a small decrease in the number of military titles after the Islamists take power. There is not a greater number of members of the MB on boards, most likely due to our the aforementioned inability to identify these individuals.

Panel B shows regressions of firm-level profitability on N_i for each accounting year during our sample. We see that the significantly higher profitability of NDP-connected firms drops sharply during the period of military rule, and the profitability of military-connected firms increases. During Islamist rule, we see a small additional decrease in the profitability of NDP-connected firms, a sharp drop in the profitability of military-connected firms, and a higher profitability for Islamic firms (though the profitability of non-connected firms increases even more during this phase).[19] Naturally, these results, which are looking over longer periods of time, could reflect other concurrent changes during these time windows. All the same, they are broadly consistent with the picture that emerges from our event studies and suggest that the changing valuations in the Egyptian stock market we document above reflect real, rather than just perceived, changes in rents captured by different groups of connected firms.[20]

In line with this interpretation, two recent studies (Diwan et al., 2015; Sahnoun et al., 2014) document in detail the microeconomic mechanisms through which rents were funnelled to NDP-connected firms during the Mubarak era. These include subsidized loans by state-owned banks, barriers to entry, lax enforcement of rules, and protection from foreign competition. Following the fall of Mubarak, there is qualitative evidence that some of these rents disappeared. For example, Ahmed Ezz, a steel magnate and senior member of the NDP, was well known for successfully opposing any amendments that would enable the Egyptian Competition Authority to harm his firms' monopoly. Following Mubarak's fall, Ezz was prosecuted and new licenses for factories competing with Ezz-owned firms were issued (El Far, 2012). Other examples include fines for anti-competitive behavior levied on Mobinil, a telecommunications provider connected to the NDP according to our data, and the prosecution of NDP connected developers for purchasing land at below-market rates from the Mubarak government.[21]

[19] In addition to affecting cash flows, changing political fortunes may also affect the discount rates of connected firms.

[20] We also looked at the mean purchases of stocks by corporate insiders for each set of connected firms during the four phases of Egypt's Arab Spring. These results presented in Appendix Table 8 show very little movement in net insider trades, suggesting that there is no tendency of insiders to divest or increase their holdings in these companies.

[21] See Bertelsmann Stiftung BTI Country Report Egypt, 2016; Al-Ahram Online on June 30, 3013, December 3, 2013 and April 8, 2014; and Daily News Egypt on April 6, 2014.

4 Street Protests and Economic Rents

Our findings in the previous section suggest that major political events of the Arab Spring impacted stock market returns, most likely because of the changing perception of the ability of connected firms to capture economic rents. We now turn to our main results, which focus on the impact of high-frequency protest activity on (perceived) rents captured by different groups of connected firms.

Our main specification takes the form

$$R_{it} = N_i'\gamma + \left(P_t \times N_i'\right)\gamma^p + X_i'\nu_t + \delta_t + \eta_s + \epsilon_{it}, \tag{2}$$

where R_{it} is as defined above (the log return of firm i on day t) and P_t denotes the (standardized) number of protesters in Tahrir Square on trading day t. In particular, in our baseline regressions, P_t is measured as the total number of protesters on that day capped at 500,000 and divided by 500,000, so that the maximum value P_t takes is 1. We cap this variable at 500,000 to reduce the impact of very large protests on a few days (we also deal with this issue by using other functional forms as discussed below).[22] N_i and X_i are again the vectors of dummies denoting affiliation to one of the three groups, and our set of standard controls, respectively. The fact that the coefficient on X_i, ν_t, is indexed by time indicates that we allow a full set of time interactions with these covariates (in some specifications also with sector fixed effects). Finally, δ_t and η_s denote, respectively, time and sector dummies.

The coefficients of interest are the entries of the vector γ^p. Under the usual assumption that there are no omitted variables conditional on our controls causing differential returns, $Cov\left(P_t \times N_i', \epsilon_{it} \mid X_i, \delta_t, \eta_s\right) = 0$, these coefficients measure the effect of the number of protesters in Tahrir Square on the relative stock market valuation of connected firms. Specifically, we require that (1) there should be no omitted variables that fluctuate at the daily frequency and are correlated with both stock returns and the number of protesters in Tahrir Square, and (2) that there is no reverse causality from daily differential returns on firms connected to different power groups to the intensity of protests.

A specific concern would be that news about the current government's popularity or performance might

[22] Because we assign the number of protesters on non-trading days to the first trading day, all protests that occur in the weeks surrounding Mubarak's fall (January 28-March 29, 2011) are assigned to March 30. The cap on our measure P_t ensures that this day does not receive a higher weight in our analysis than other large protest days shown in Figure 1.

impact stock returns of different types of firms while also triggering protests. Though this concern is potentially important, we believe that our use of daily data greatly alleviates it. In particular, there is a considerable degree of randomness in which days protesters are able to solve the collective action problem, organize, and mobilize, and this variation will be quite important for our results.[23] Relatedly, we will demonstrate that future protests have no predictive power for current stock market valuations, weighing against concerns about omitted factors and reverse causality.[24]

Columns 1-4 in Table 6 show estimates of equation (2) for each of the four phases of Egypt's Arab Spring. Column 1 shows a negative and statistically significant effect of street protests on the stock market valuation of NDP-connected firms during the first phase of the revolution. Given that $P_t = 1$ corresponds to 500,000 (or more) protesters turning up to Tahrir Square, the coefficient (-1.614 s.e.=0.602) shows that the presence of 500,000 or more protesters in Tahrir Square is associated with a 1.6% decrease in the valuation of NDP-connected firms on that day. The cumulative number of protesters during this first phase according to our standardized measure is 1.22, such that the cumulative impact of street protests on the value of NDP-connected firms is a 1.95% decrease during this phase. We find no statistically significant impact on firms connected to the two rival groups.

Column 2 shows the same specification for the second phase, under military rule. Now we see a substantial impact on military-connected firms (-0.889, s.e.= 0.326) and no significant effect on NDP-connected and Islamic firms. The cumulative impact of street protests on the value of military-connected firms is a decrease of 4.7% during this phase.

Column 3 looks at the third phase (Islamist Rule), and finds that none of the three effects of street protests are statistically distinguishable from zero, except for a marginally significant, positive effect on NDP-connected firms (0.672, s.e.=0.382). A possible reason for this lack of significant results in the third phase is that during this period, Tahrir Square saw both pro- and anti-Islamist protests, breaking the usual pattern that protests in Tahrir square were generally directed against the government then in power.

[23]If protests were anticipated in advance, this would also imply that future protests should impact current stock market prices, a pattern for which we find no support as we explain next.

[24]A related concern is that protests are often led by a small group of "leaders," and one might worry whether these leaders have any information about the vulnerability of the incumbent group. We do not see this possibility as a threat to our empirical strategy. First, the fact that the protests have leaders does not change the fact that the protests are shifting the balance of power in society (and our results are a testament to that fact). Second, if the leaders' superior information about regime vulnerability were an important factor, we would again expect our specification tests to show the correlation between current stock market returns and future protests, which is not the pattern we see in the data.

Column 4 looks at the the fourth (post-Islamist) phase, in which pro- and anti-Islamist camps separated geographically, and we see that the clear relationship between the number of protesters and the stock market valuation of firms connected to the target group of the protests reemerge. In particular, in this column, we include protests in Rabaa Square, which became the location of pro-Islamist demonstrations, whereas those in Tahrir Square were generally anti-Islamist. Consistent with this, Tahrir Square protests have a negative effect, whereas Rabaa Square protests have a positive effect on Islamic-connected firms (-1.332, s.e. =0.815, and 27.85, s.e.=12.89, respectively).

A noteworthy pattern in Table 6 is that, with the exception of the third phase of the revolution (Islamist Rule), and consistent with our event study results, we find a significantly negative effect of protests in Tahrir Square on the relative stock market valuation of firms connected to the incumbent regime, and generally no effect on firms connected to the rival (non-incumbent) groups. Motivated by this, in Table 7, we adopt a specification analogous to that in Table 4 where we pool data from all four phases and include only two dummies, one for being connected to the group that is currently in power (incumbent), and the other for being connected to one of the other two rival (non-incumbent) groups. As before, the incumbent group during Mubarak's fall is the NDP; during military rule it is the military; during Islamist rule it is the Islamists. For the post-Islamist rule, we still code the Islamists as the "incumbent" group because anti-Islamist protests in Tahrir square continued for several weeks after Mursi's fall (until the end of our sample). We additionally control for interactions of pro-Islamist protests in Rabaa Square during this period with the incumbent and connected (non-incumbent) dummies. Non-connected firms are again in the regression, so all coefficients are relative to the changes in the values of non-connected firms.

Column 1 of Table 7 relates returns to a full set of time and sector fixed effects and the interaction of the two dummies with the number of protesters in Tahrir Square. It shows a negative and statistically significant effect of the number of protesters in Tahrir Square on the relative market valuation of firms connected to the incumbent government (-0.879, s.e.=0.243), and no positive impact on firms that are connected to the other two rival groups (-0.281, s.e.=0.205). Column 2 estimates our baseline specification allowing fully flexible effects over time from our set of controls (that is, it includes the interaction of a full set of time dummies with the control vector X_i). The estimated effect of the number of protesters on the returns on firms connected to the incumbent government drops only a little to -0.751 (s.e.=0.254) and the effect on the returns of firms connected to the rival groups remains negative and insignificant at (-0.160, s.e.=0.216).

If street protests result in a pure reallocation of rents from incumbent to rival connected groups, the two coefficients weighted, respectively, by the market capitalization of incumbent and connected (non-incumbent) firms across the sample should be equal and of opposite sign. As shown by the middle two rows of the table, we reject this hypothesis with a p-value of 0.034. We also reject the hypothesis that the two coefficients are equal and of opposite sign with a p-value of 0.011. These results thus suggest that, while street protests significantly decrease the market valuation of incumbent firms, they have no major effect on firms connected to non-incumbent groups. This pattern is broadly consistent with our previous results, but can be seen more clearly when pooling data across the four phases of Egypt's Arab Spring.

Column 3 drops all dates identified in our event analysis as involving changes in government or *de jure* institutions plus the next three trading days (in particular, we drop the fall of Mubarak, the first and the second round of the presidential elections, the passing of the MB's constitution, and the military coup against Mursi). In column 4, we go one step further and drop *all* of the events studied in the previous section plus the following three trading days. These two specifications illustrate that our results in this section are not just a reflection of the stock market responses of connected firms in the context of the event studies already discussed in the previous section. Rather, the fact that the results in columns 3 and 4 are very similar to the baseline suggests that protests have a major impact on the relative stock market valuation of firms connected to the incumbent group—even when there are no changes, and no clear expectation of imminent changes, in regime or political institutions. This pattern bolsters our interpretation that these findings do not just reflect the consequences of changes (or expected changes) in regime or *de jure* political institutions. Instead, our interpretation is that, consistent with the findings in Collins and Margo (2007) and Madestam et al. (2013), there is also some element of current protests signaling future mobilization and thus impacting the perception of the extent of rents that can be captured by firms connected to politically powerful groups.

Robustness and Timing. The rest of the table probes the robustness of this result. To address the concern that the number of protesters in Tahrir Square may be correlated with specific news about firms connected to the incumbent regime (such as strikes at the firm, CEO departures, or asset freezes), we also include a specification that drops a given firm on all dates on which its ticker symbol is mentioned in the leading Arabic-language equity news stream (*Mubasher*).[25] This reduces the number of observations by 5,408, but has little impact on the coefficient of interest (which is now -0.766, s.e.=0.259).

As further robustness checks, column 5 adds a full set of firm fixed effects. Column 6 adds a quadratic in all of our controls (size, leverage, and the three betas), again fully interacted with time dummies. Both variations have little impact on our coefficient estimates.

Column 7 goes one step further and includes interactions between the number of Tahrir Square protesters and the 16 sector dummies (as well as the controls already included in column 2). This reduces the coefficient on the incumbent times protesters interaction to -0.483, although it remains statistically significant at 10% (s.e. = 0.247). The slight loss of precision in this fairly demanding specification (with 3608 control variables) is most likely attributable to loss of statistical power. This interpretation is confirmed by column 8, which continues to include the interactions between the number of protesters and the 16 sector dummies but drops the other time-interactive controls, restoring the coefficient of interest to a precisely-estimated -0.685 (s.e. = 0.234). Column 9 goes even further and includes a full set of interactions between the time and sector dummies (which of course subsumes interactions with the numbers of protesters). The estimate of the impact of protests on the relative stock market value of firms connected to the incumbent group continues to be significant at 5 percent in this very demanding specification (-0.548, s.e. = 0.271).

Panel A of Table 8 turns to an investigation of whether current protests or leads or lags of protests impact the stock market valuation of connected firms. Because of limited liquidity in the Egyptian Stock Exchange and because protests often peak after trading hours, the impact of shifts in the balance of political power might be transmitted to stock market valuations over several days, making lags of protests statistically significant. If, on the other hand, leads were statistically significant, this would signal a failure of our identification assumption—in particular, it would make it likely that both protests and stock market valuations are responding to some other slow-moving change that is not being controlled for in our regressions. The results in Table 8 document that the impact of current protests is robust, and that there is no evidence of leads of protests predicting stock market reactions (i.e., no evidence that *current* stock market outcomes are being predicted by *future* protests). This pattern bolsters our confidence in the results presented so far, and

[25] This was obtained by scraping the news histories of all firms in our sample back to Jan 1, 2010 from http://english.mubasher.info/EGX/stocks. See Appendix Table 11 for details on this specification.

weighs against an interpretation in which protests and stock market valuations of different types of firms are being driven by omitted factors or news about other events weakening the regime in power.

The results in columns 3 and 4 of Table 8 indicate that the one-day lag of protests is indeed statistically significant and the second lag is marginally significant, but there is no evidence of a statistically significant effect from longer lags, which is encouraging for our interpretation.

Appendix Table 9 shows results of a portfolio-based estimation where we regress the returns on portfolios of incumbent, other connected, and non-connected firms on the number of protesters in Tahrir Square and test for differences in coefficients. This procedure yields results very similar to our baseline specification, but again at a higher level of statistical significance, reflecting the aforementioned negative correlation of residuals across connected firms.[26]

An Additional Prediction. If street protests indeed constrain rent-seeking, we should expect their effects to be more pronounced for incumbent firms that used to extract more rents pre-revolution. In order to test this prediction, we collected bank loans data from Zawya for the year 2010 (i.e., immediately before the revolution). As argued by Diwan et al. (2015), cheap loans extended by government-controlled banks were a particularly common form of rent transfers during the Mubarak era. We should therefore see larger effects of street protests on incumbent firms with more bank loans. This expectation is confirmed in Panel B of Table 8, where we add the interaction between bank-loans as a share of the firm's total assets in 2010 with the number of protesters in Tahrir square and the incumbent dummy. In all specifications, this triple interaction is negative, and it is statistically significant at the 5 or 10% level in all specifications except for column 2.

[26] Additional robustness checks are included in the Appendix. First, we verify that our baseline specification does not tend to over-reject the null by randomly assigning protesters from the empirical distribution of number of protesters between Jan 1, 2011 and July 30, 2013 to trading days between Jan 1 and Nov 30, 2010, and repeating our estimation. Appendix Figure 4 shows that there is no over-rejection in this case. Appendix Table 10 shows very similar results from models that are estimated separately for each of the four phases of Egypt's Arab Spring. Appendix Table 11 demonstrates that the results are unchanged when we include a full set of interactions between the day of the week and the number of protesters in Tahrir Square, control flexibly for alternative asset pricing factors (Fama and French, 1992; Carhart, 1997), interact our "incumbent" and "other connected" dummies with the the stock's daily trading volume, and use Newey-West standard errors. Appendix Table 12 shows that our results are robust to dropping either the post-Islamist phase or both the Islamist and the post-Islamist periods, addressing potential concerns that our coding of Islamic firms is likely to be subject to greater error, as well as any complications resulting from simultaneous pro- and anti-Islamist protests during Mursi's rule. Appendix Table 13 shows the robustness of our results to functional forms, using the (non-capped) level of protesters, the log of protesters, and a dummy for protests exceeding 100,000 participants. In addition, we estimated the parameters of a Box-Cox transform for the specification in column 1 of Table 7 (without the covariates, $X_i'\nu_t$). The maximum likelihood estimate of the exponent on P_t is 1.212 (s.e.=0.832). We cannot therefore reject the hypothesis that the relationship between our main variable (the incumbent dummy interacted with the number of protesters capped at 500,000) and differential stock returns is linear. Finally, Appendix Figures 5 and 6 show that all results are also robust to dropping individual firms and re-classifying individual connected firms as unconnected.

Interpretation We draw three main conclusions from the results presented in this section. First, consistent with our event study results, street protests appear to affect the stock market valuation of firms connected to the three power groups relative to non-connected firms.

Second and most importantly, the *intent* of protesters appears to have real effects: in the first and second phases of the revolution, protests in Tahrir Square directed against the incumbent government (first Mubarak's and then military's) tend to reduce the stock market value of firms connected to the incumbent government. In the fourth phase, anti-Islamist protesters in Tahrir Square reduce the relative market valuations of Islamic firms, whereas pro-Islamist protesters in Rabaa Square appear to increase these valuations. This pattern is confirmed by the results in Table 7, which document that the effect is on firms connected to the incumbent group, while there appears to be no significant effect on the value of connections to the two rival (non-incumbent) groups.

Third, this pattern of results is not consistent with the differential effects of protests on the stock market valuations of connected firms being *entirely* due to the reallocation of a fixed amount of rents among listed firms. Had this been the case, we would have found a positive impact on the relative valuation of firms connected to rival groups.

Our overall interpretation is that these results reflect the expectation that street protests limit the ability of politically connected firms to extract rents in the future. This is likely driven by both their effect on potential future changes in regime and *de jure* institutions (especially since protests have sometimes been followed by such major changes, most notably with Mubarak's fall), and the possibility that *de facto* power emanating from street protests might directly curtail future rent-seeking by these connected firms.

5 Social Media and Protests

In this section, we use our Twitter data to investigate whether social media activity predicts protests; to analyze whether discontent voiced on social media impacts stock market returns with or without simultaneously controlling for street protests; and to show that the cohesiveness of the opposition (as reflected in the pattern of retweeting) interacted crucially with the impact of protest activity on differential returns of connected firms.

Panel A of Table 9 shows that there is a positive association between Tahrir hashtags, our main measure of social media activity related to the protests, and the number of protesters in Tahrir Square during each of the four phases of Egypt's Arab Spring. To facilitate the interpretation of the coefficients, we standardize both the left- and the right-hand-side variables throughout the table by subtracting the mean and dividing by the standard deviation. During the first phase of the revolution (Mubarak's fall), the authorities blocked access to Twitter between January 25 and February 2, 2011 (on some days during this window, they also shut down the entire internet and some phone services). Although tweeting by telephone during this period was still possible, we control for limited access to social media and the internet by adding a dummy for this period on the right-hand side. Interestingly, the coefficient on this dummy is positive and marginally statistically significant, suggesting that invasive measures that cut access to social media may have backfired in this instance.

In all phases, with the possible exception of the post-Islamist one (where we have few observations), we see a strong correlation between this measure of social media activity (related to protests) and the protests themselves. Column 5 pools all phases together and confirms the pattern. The point estimate (0.219, s.e.=0.075) suggests that a one standard deviation increase in the number of tweets is associated with a 0.219 standard-deviation increase in the number of protesters in Tahrir Square.

The results in columns 1-5 might be reflecting the fact that protesters turn up to Tahrir Square and then report their presence on Twitter using the Tahrir hashtag. Columns 6-8 investigate this issue by studying whether it is the leads or lags of hashtags that are correlated with protests. Reassuringly, we find that it is the lags of Tahrir hashtags that matter for protests more than the current or the lead values. If it were simply that people who are participating in protests are also tweeting about it, then there should be a larger contemporaneous correlation between the two variables. The lead being the dominant variable, on the other hand, would suggest that both of these variables might be reflecting some other news or omitted factors. Instead the pattern we find in the data, with the lagged hashtags being the dominant variable, supports the view that social media is being used as a vehicle for mobilizing people—who then turn out to Tahrir Square the following day.[27]

[27]The fact that activity on Twitter can be used to predict protests suggests that investors may have been able to trade on this information in real time. However, given the uniqueness of this historical episode and the complexity involved with obtaining and selectively processing the relevant Twitter data (it took us twelve months), we do not believe that such a strategy was

In Panel B, we look at the amount of retweeting of tweets by opposition leaders, which we interpret as a measure of general discontent with the government in power and support for the opposition. We find very similar results, suggesting that general discontent is also associated with greater numbers of protesters in Tahrir Square. When we turn to timing, however, the evidence is less clear-cut. Because of serial correlation, when any two of the current, lag and lead values are included together, neither one is individually statistically significant (though they jointly are).

When we include both the Tahrir hashtags and the retweeting variables together in Panel C, we find that the coefficient on Tahrir hashtags remains statistically significant at the 1% level (0.140, s.e.=0.050) while the coefficient on retweets of opposition is now only marginally significant (0.202, s.e.=0.107). This pattern is plausible since Tahrir hashtags are presumably more directly related to the protests than the more general discontent captured by our opposition retweets variable.

Columns 1-4 of Table 10, however, show that social media activity has no impact on differential stock market returns with or without controlling for actual street protests.[28] Though this result might reflect differential measurement error (e.g., perhaps our social media variables are measured with greater error than the number of protesters), it is also consistent with the view that what matters for the actual balance of power—and the resulting economic rents—is the mobilization of people in the street, and not their social media activity or their general discontent. This is, in particular, consistent with the fact that discontent with Mubarak's regime has been deep-rooted in Egyptian society for decades, but had little impact on actual politics until it poured into the streets, and also suggests that street protests against unpopular regimes may play a special role, because they involve large-scale coordination and may provide important information to participants in this protests and others in society (perhaps by making the discontent "common knowledge").[29]

In column 5, we drop our control for the number of protesters in Rabaa Square and instead use our Twitter data to construct a measure of the nature and cohesion of the opposition. In particular, we construct

widely implemented.

[28]For the purposes of this comparison between Twitter-based measures and the number of protesters in Tahrir Square we treat all independent variables symmetrically and do not cap the number of protesters at 500,000. Instead, we standardize the number of retweets, Tahrir hashtags, and Tahrir protesters by deducting their respective sample means and dividing by their respective sample standard deviations. This is why the magnitude of coefficients differs from that in Table 7.

[29]Econometrically, this means that social media activity can be thought of consisting of two components, one that predicts protests and thus excess returns of connected firms, and one that does not. Because of the presence of the latter component, social media activity overall may have no or little predictive power for excess returns of connected firms.

a measure we call "opposition turnover," which we define (in analogy to an employee turnover rate) as the number of Twitter users who retweet a tweet of an opposition leader in $t-1$ but not in t divided by the average number of retweeters on the two days.[30] At one extreme, when the composition of retweeters changes from day to day, this will indicate a much less cohesive opposition (with fewer dedicated members) relative to the other extreme where the same people retweet more systematically. It might then be reasonable to imagine that a less cohesive opposition will not be able to exert as much *de facto* power as a more cohesive one. Our results in this table confirm this expectation. Though the opposition turnover variable does not have much of an effect by itself, when this turnover variable is high, protests have a more limited impact on the rents captured by firms connected to the incumbent:[31] The interaction between the incumbent dummy, the number of protesters in Tahrir Square, and the opposition turnover variable is positive and significant at the 10% level (0.138, s.e.=0.075). The estimate implies that a one standard deviation increase in the opposition turnover rate (3.73) is associated with a 34% drop in the effect of street protests on the relative stock market valuations of firms connected to the incumbent group.

6 Conclusion

The Arab Spring was a momentous set of changes, involving an unparalleled mobilization of people in many parts of the Arab world. In Egypt, it led to the downfall of the regime of Hosni Mubarak, who had ruled the country as a *de facto* dictator for 30 years. The broad-based mobilization unleashed by these events continued after Mubarak's fall, underscoring the importance (but in many instances also the limitations) of the power of the street. Several theories in social science emphasize the role of *de facto* power resulting from groups being able to solve their collective action problems and mobilizing in the street, in changing economic allocations, and even in changing the *de jure* distribution of political power. Nevertheless, there is only limited evidence in economics and other social sciences showing that changes in the *de facto* political

[30]Formally, denoting the set of opposition retweeters in t as T_t, we have Opposition $\text{Turnover}_t = \frac{|T_{t-1} \cap T_t|}{0.5\left(|T_{t-1}|+|T_t|\right)} 100$, where $T_{t-1} \cap T_t$ denotes the intersection of T_{t-1} and the complement of T_t.

[31]It is reasonable that it should be the triple interaction of the opposition-turnover variable with protests and the incumbent and connected (non-incumbent) dummies that should matter — not the opposition-turnover variable interacted with these dummies for connected firms. The interaction between opposition turnover and the dummies for connected firms correspond to the impact of opposition turnover when there are no protesters. But since when there are no protesters, there is no pressure from the street on the incumbent government, the cohesion of the opposition should also not matter, which is the pattern we find.

power of different groups and political mobilization directly matter for any economic outcome.

In this paper, we provide evidence that protests have played an important role in curtailing rents captured by politically connected firms in Egypt (or at the very least, the stock market participants' perceptions of these rents). These results are unlikely to be driven by reverse causality or some omitted factors moving stock market returns first and subsequently triggering protest activity. We further find that the lower stock market valuations of firms connected to the incumbent group (relative to non-connected firms) do not appear to have been compensated by higher relative values for firms connected to the rival (non-incumbent) groups, and the impact of street protests on rents also holds during periods when there were no changes in formal institutions or government and when no such changes appeared to be forthcoming soon.

The totality of this evidence motivates our interpretation that though some of the differential returns were undoubtedly related to the market's perception that as one group falls another will rise, they are unlikely to be just a consequence of a given amount of rents being reallocated between different groups of connected firms. Rather, we interpret these results as reflecting, at least in part, stock market participants' perceptions that the ability of connected firms to siphon off rents will be curtailed by a combination of future institutional changes and heightened mobilization following these major protests.

Finally, we also document that, consistent with popular media coverage of Egypt's Arab Spring, social media played some role in the protests. Both tweeting activity related to Tahrir Square and retweeting of opposition leaders' tweets, which we interpret as a measure of general discontent about the government in power, predict protests. Though our results confirm the importance of social media in the organization of protests, they do not support the view that social media has fundamentally transformed the problem of mass mobilization against authoritarian regimes, since we find it is street protests, not various measures of Twitter activity, that influences the stock market's perception of rents captured by different groups of connected firms.

References

Abadie, A., A. Diamond, and J. Hainmueller (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American Statistical Association 105*(490), 493–505.

Abadie, A. and J. Gardeazabal (2003). The economic costs of conflict: A case study of the basque country. *American Economic Review 93*(1), 113–132.

Acemoglu, D., S. Johnson, A. Kermani, J. Kwak, and T. Mitton (2016). The value of connections in turbulent times: Evidence from the United States. *Journal of Financial Economics 121*(2), 368–391.

Acemoglu, D. and J. A. Robinson (2000). Why did the west extend the franchise? growth, inequality and democracy in historical perspective. *Quarterly Journal of Economics 115*(4), 1167–1199.

Acemoglu, D. and J. A. Robinson (2006). *Economic Origins of Dictatorship and Democracy*. Cambridge University Press, Cambridge; New York.

Adamic, L. A. and N. Glance (2005). The political blogosphere and the 2004 U.S. election: Divided they blog. In *Proceedings of the 3rd International Workshop on Link Discovery*, pp. 36–43. ACM.

Aidt, T. S. and R. Franck (2013). How to get the snowball rolling and extend the franchise: Voting on the great reform act of 1832. *Public Choice 155*(3-4), 229–250.

Aidt, T. S. and R. Franck (2015). Democratization under the threat of revolution: evidence from the great reform act of 1832. *Econometrica 83*(2), 505–547.

Aidt, T. S. and P. S. Jensen (2013). Democratization and the size of government: Evidence from the long 19th century. *Public Choice 157*(3-4), 511–542.

Akey, P. (2015). Valuing changes in political networks: Evidence from campaign contributions to close congressional elections. *Review of Financial Studies 28*(11), 3188–3223.

Alesina, A., S. Özler, N. Roubini, and P. Swagel (1996). Political instability and economic growth. *Journal of Economic Growth 1*(2), 189–211.

Alesina, A. and R. Perotti (1996). Income distribution, political instability, and investment. *European Economic Review 40*(6), 1203–1228.

Becker, B., D. Bergstresser, and G. Subramanian (2013). Does shareholder proxy access improve firm value? evidence from the business roundtable's challenge. *Journal of Law and Economics 56*(1), 127–160.

Bidner, C. and P. Francois (2013). The emergence of political accountability. *Quarterly Journal of Economics 128*(3), 1397–1448.

Bunkanwanicha, P. and Y. Wiwattanakantang (2009). Big business owners in politics. *Review of Financial Studies 22*(6), 2133–2168.

Campante, F. R. and D. Chor (2012). Why was the arab world poised for revolution? schooling, economic opportunities, and the arab spring. *Journal of Economic Perspectives 26*(2), 167–188.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance 52*(1), 57–82.

Chaney, E. (2012). Democratic change in the arab world, past and present. *Brookings Papers on Economic Activity*.

Chaney, E. (2013). Revolt on the nile: Economic shocks, religion, and political power. *Econometrica 81*(5), 2033–2053.

Chekir, H. and I. Diwan (2015). Crony capitalism in Egypt. *Journal of Globalization and Development*.

Collins, W. J. and R. A. Margo (2007). The economic aftermath of the 1960s riots in american cities: Evidence from property values. *The Journal of Economic History 67*(4), 849–883.

Dinç, I. S. (2005). Politicians and banks: Political influences on government-owned banks in emerging markets. *Journal of Financial Economics 77*(2), 453–479.

Diwan, I., P. Keefer, and M. Schiffbauer (2015). Pyramid capitalism: Cronyism, regulation, and firm productivity in Egypt. *World Bank, Policy Research Working Paper Series: 7354*.

Dube, A., E. Kaplan, and S. Naidu (2011). Coups, corporations, and classified information. *Quarterly Journal of Economics 126*(3), 1375–1409.

Edmond, C. (2013). Information manipulation, coordination, and regime change. *The Review of Economic Studies 80*(4), 1422–1458.

El Far, M. (2012). The egyptian state of competition: The steel market case study. *Available at SSRN 2515698*.

Enikolopov, R., M. Petrova, and K. Sonin (2016). Social media and corruption. *CEPR Discussion Papers: 11263*.

Faccio, M. (2006). Politically connected firms. *American Economic Review 96*(1), 369–386.

Faccio, M., R. W. Masulis, and J. McConnell (2006). Political connections and corporate bailouts. *The Journal of Finance 61*(6), 2597–2635.

Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *The Journal of Finance 47*(2), 427–465.

Fama, E. F. and K. R. French (2000). Forecasting profitability and earnings*. *The Journal of Business 73*(2), 161–175.

Fearon, J. D. (2011). Self-enforcing democracy. *Quarterly Journal of Economics 126*(4), 1661–1708.

Ferguson, T. and H.-J. Voth (2008). Betting on Hitler: The value of political connections in Nazi Germany. *Quarterly Journal of Economics 123*(1), 101–137.

Fisman, R. (2001). Estimating the value of political connections. *American Economic Review 91*(4), 1095–1102.

Gilli, M. (2012). A simple model of repression and revolt in autocracies applied to the arab spring. *International Game Theory Review 14*(4), 1–29.

Greenwood, R. (2005). Short- and long-term demand curves for stocks: Theory and evidence on the dynamics of arbitrage. *Journal of Financial Economics 75*(3), 607–649.

Haber, S., N. Maurer, and A. Razo (2004). *The Politics of Property Rights: Political Instability, Credible Commitments, and Economic Growth in Mexico, 1876-1929*. Cambridge University Press, New York; Cambridge.

Halberstam, Y. and B. Knight (2014, November). Homophily, group size, and the diffusion of political information in social networks: Evidence from twitter. Working Paper 20681, National Bureau of Economic Research.

Harb, I. (2003). The egyptian military in politics: Disengagement or accommodation? *Middle East Journal 57*(2), 269–290.

Henry, C. M. and R. Springborg (2010). *Globalization and the Politics of Development in the Middle East*, Volume 1. Cambridge University Press.

Heydemann, S. (2004). *Networks of privilege in the Middle East: the politics of economic reform revisited*. Palgrave Macmillan.

Johnson, S. and T. Mitton (2003). Cronyism and capital controls: Evidence from malaysia. *Journal of Financial Economics 67*(2), 351–382.

Karolyi, G. A. (2015). *Cracking the emerging markets enigma*. Oxford University Press, USA.

Kent, L. and T. Phan (2014). A model of the arab spring revolutions: Why did the arab spring turn out differently across countries? *Working Paper*.

Khwaja, A. I. and A. Mian (2005). Do lenders favor politically connected firms? rent provision in an emerging financial market. *Quarterly Journal of Economics 120*(4), 1371–1411.

King, G., J. Pan, and M. E. Roberts (2013). How censorship in china allows government criticism but silences collective expression. *American Political Science Review 107*(2), 326–343.

Knight, B. (2006). Are policy platforms capitalized into equity prices? evidence from the bush/gore 2000 presidential election. *Journal of Public Economics 90*(4), 751–773.

Kricheli, R., Y. Livne, and B. Magaloni (2010). Taking to the streets: Theory and evidence on protests under authoritarianism. In *APSA 2010 Annual Meeting Paper*, pp. 1–45.

Kuran, T. (1989). Sparks and prairie fires: A theory of unanticipated political revolution. *Public Choice 61*(1), 41–74.

Kuran, T. (1991). Now out of never: The element of surprise in the East Europen Revolution of 1989. *World Politics 44*(01), 7–48.

Leuz, C. and F. Oberholzer-Gee (2006). Political relationships, global financing, and corporate transparency: Evidence from indonesia. *Journal of Financial Economics 81*(2), 411–439.

Lohmann, S. (1994). The dynamics of informational cascades: The monday demonstrations in leipzig, east germany, 1989-91. *World Politics 47*(1), 42–101.

Madestam, A., D. Shoag, S. Veuger, and D. Yanagizawa-Drott (2013). Do political protests matter? evidence from the tea party movement. *Quarterly Journal of Economics 128*(4), 1633–1685.

Overland, J., K. L. Simons, and M. Spagat (2005). Political instability and growth in dictatorships. *Public Choice 125*(3-4), 445–470.

Rijkers, B., C. Freund, and A. Nucifora (2014). The perils of industrial policy evidence from Tunisia. Technical report, mimeo, The World Bank.

Roberts, B. E. (1990). A dead senator tells no lies: Seniority and the distribution of federal benefits. *American Journal of Political Science 34*(1), 31–58.

Roll, S. (2010). 'finance matters!' the influence of financial sector reforms on the development of the entrepreneurial elite in egypt. *Mediterranean Politics 15*(3), 349–370.

Sahnoun, H., P. Keefer, M. Schiffbauer, A. Sy, and S. Hussain (2014). *Jobs or Privileges: unleashing the employment potential of the Middle East and North Africa*. World Bank Publications.

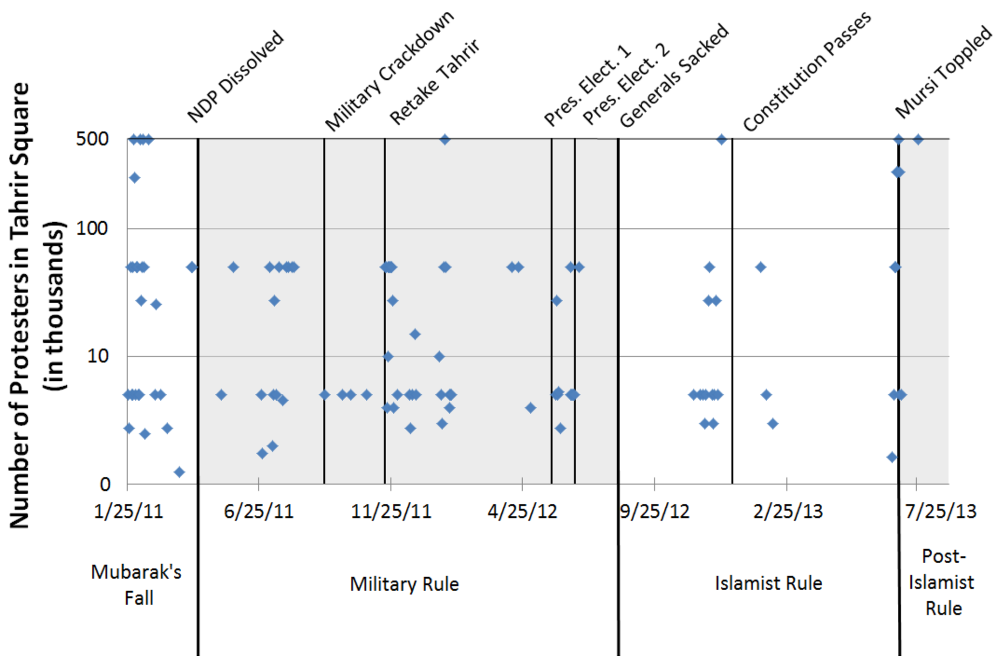
Schipper, K. and R. Thompson (1983). The impact of merger-related regulations on the shareholders of acquiring firms. *Journal of Accounting research*, 184–221.

Snowberg, E., J. Wolfers, and E. Zitzewitz (2007). Partisan impacts on the economy: Evidence from prediction markets and close elections. *Quarterly Journal of Economics 122*(2), 807–829.

Svensson, J. (1998). Investment, property rights and political instability : Theory and evidence. *European Economic Review 42*(7), 1317–1341.

Weber, I., V. R. K. Garimella, and A. Batayneh (2013). Secular vs. islamist polarization in Egypt on Twitter. In *Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, pp. 290–297. ACM.

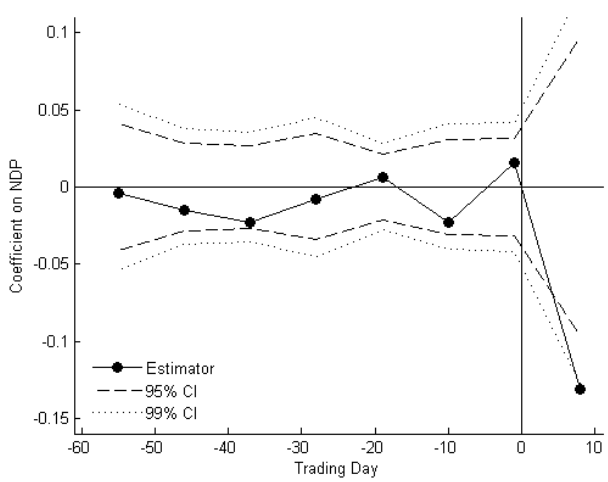
Figure 1: Number of Protesters in Tahrir Square



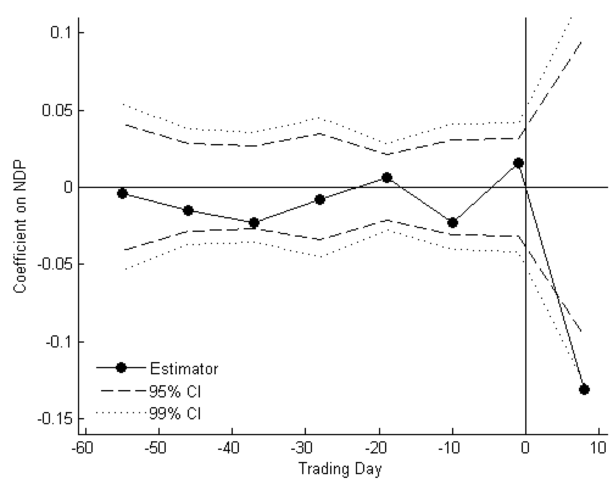
Note: Number of protesters in Tahrir Square on each day between January 1, 2011, and July 30, 2013. See section 2 of the main text for details.

Figure 2: Placebo Regressions in Pre-Event Windows

Panel A: *OLS*



Panel B: *Synthetic Matching Estimator*



Note: Panel A shows coefficients and 99%, and 95% confidence intervals on the dummy variable for NDP-connected firms in specifications corresponding to column 2 of Table 2. The figure shows coefficients for seven consecutive event windows prior to Jan 25, 2011 (event trading day 0). Each event window consists of 8 consecutive trading days. For comparison, the coefficient on the far-right side depicts the treatment effect of Mubarak's fall shown in column 2 of Table 2. Panel B shows the same placebo experiment as Panel A using the synthetic matching estimator described in section 3. The coefficient on the far-right side depicts the treatment effect of Mubarak's fall shown in column 6 of Table 2.

Table 1: Summary Statistics

Panel A: Firm Characteristics by Network

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Share			Mean		
	N	Market Cap	Size	Leverage	β^{World}	β^{Egypt}	β^{Unrest}
All	177	1.00	800.87	0.39	0.53	0.79	0.0023
s.d.			1986.15	1.05	0.88	0.80	0.0153
Unconnected	114	0.41	465.46	0.37	0.51	0.79	0.0028
s.d.			1431.53	1.24	0.95	0.95	0.0192
Connected	63	0.59	1412.17	0.43	0.57	0.79	0.0015
s.d.			2627.07	0.59	0.77	0.47	0.0042
NDP	22	0.33	2436.62	0.65	0.58	0.61	0.0003
s.d.			3429.74	0.61	1.23	0.50	0.0053
Military	33	0.12	240.11	0.25	0.56	0.88	0.0015
s.d.			340.43	0.44	0.43	0.45	0.0035
Islamic	13	0.19	2481.98	0.49	0.77	0.68	0.0019
s.d.			2780.73	0.67	1.51	0.64	0.0058

Notes: The table presents means and standard deviations of firm characteristics on January 1, 2011, before the beginning of Egypt's Arab Spring. The first panel gives statistics for all firms. The second and third panels show the same statistics for connected vs. non-connected and NDP-, Military-, and Islamic-connected firms, respectively. Among the 13 Islamic firms, 5 are connected to NDP and the other 8 are connected to neither NDP nor the military. Share Market Cap denotes the share of each group of firms in the total market capitalization of all firms in our sample on January 1, 2011. Size is a firm's book value in millions of Egyptian pounds. Leverage is total debt over total assets. β^{World} and β^{Egypt} denote firms' beta with respect to the MSCI-world and -Egypt indices, respectively. Both variables are calculated using return data for the 2010 calendar year. β_i^{Unrest} denotes our measure of the sensitivity of a firm's return to general unrest in the country. It is calculated by regressing a firm's return on a dummy variable that is one on the two trading days that follow strikes, boycotts, riots, and instances of ethnic clashes between Muslims and Christians that occurred between January 1, 2005, and December 31, 2010.

Table 1: Summary Statistics (continued)

Panel B: Summary Statistics by Phase of Egypt's Arab Spring

	(1)	(2)	(3)	(4)	(5)
	Mubarak's Fall	Military Rule	Islamist Rule	Post-Islamist	All Phases
Date Range	01/01/11 -04/17/11	04/18/11 -08/12/12	08/13/12 07/04/13	07/05/13 07/29/13	01/01/11 07/29/13
Trading Days	38.00	323.00	219.00	16.00	596.00
Means per Trading Day					
Tahrir Protesters ('000)	838.07	13.69	23.57	31.88	70.37
Rabaa Protesters ('000)	0.00	0.00	0.46	6.44	0.34
Retweets of Opposition Leaders	1.74	3.31	5.56	12.48	4.28
Tahrir Hashtags	0.64	1.15	0.77	2.31	1.01
Opposition Turnover Rate	5.43	8.00	10.12	18.57	8.90
Daily Mean Return on Portfolio of					
All Connected Firms	-0.60	-0.09	-0.01	0.18	-0.08
NDP	-1.05	-0.09	-0.00	0.08	-0.11
Military	-0.31	-0.09	-0.03	0.24	-0.07
Islamic	-1.01	-0.04	-0.00	0.22	-0.08
Unconnected Firms	-0.48	-0.15	-0.04	0.32	-0.12
All Firms	-0.52	-0.12	-0.03	0.26	-0.10
Incumbent Group	NDP	Military	Islamic	Islamic	N/A

Notes: The table presents the number of trading days and means per trading day of time-series variables used in our analysis by phase of Egypt's Arab Spring. Columns 1-4 show statistics for each of the four phases, whereas column 5 gives statistics for all four phases combined. Tahrir Protesters ('000) and Rabaa Protesters ('000) give the number of protesters in thousands in Tahrir and Rabaa Square, respectively. Retweets of Opposition Leaders refers to the number of retweets received by a list of prominent members of the opposition. Note that this list changes as groups move in and out of power; see Appendix A.4 for details. Tahrir Hashtags denotes the number of tweets containing a hashtag containing the word "Tahrir." Opposition Turnover Rate is measured as the number of Twitter users who retweet a tweet of an opposition leader in $t-1$ but not in t, divided by the average number of retweeters on the two days in percent. Throughout, we assign tweets made during non-trading days and the number of protesters turning out on non-trading days to the following trading day. Daily Mean Returns denotes the returns in percent on an equally weighted portfolio of all connected firms, NDP-connected firms, military-connected firms, Islamic firms, non-connected firms, and all firms, respectively. Incumbent group denotes the group (NDP, Military, Islamist) that is the target of protests in Tahrir Square during each of the four phases of Egypt's Arab Spring.

Table 2: Mubarak's Fall

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				CR[0,8]			CAR[0,8]
NDP	-0.086*	-0.131**	-0.142**	-0.131**	-0.142**	-0.200***	-0.145**
	(0.049)	(0.049)	(0.059)	(0.046)	(0.054)	[-0.099,0.101]	(0.056)
Military	0.048*	0.032	0.075**	0.032	0.035	0.053	0.051
	(0.028)	(0.030)	(0.021)	(0.026)	(0.033)	[-0.066,0.082]	(0.035)
Islamic	-0.031	-0.064	-0.058	-0.064	-0.090	-0.159***	-0.125*
	(0.054)	(0.051)	(0.063)	(0.041)	(0.058)	[-0.107,0.130]	(0.066)
β^{World}		0.037**	0.023	0.037	0.050**		0.132**
		(0.016)	(0.023)	(0.023)	(0.013)		(0.046)
β^{Egypt}		-0.028	-0.021	-0.028	-0.093**		
		(0.018)	(0.025)	(0.023)	(0.030)		
β^{Unrest}		2.134*	0.897	2.134	1.812		11.219**
		(1.182)	(1.337)	(2.253)	(2.039)		(4.632)
Size		0.024**	0.022**	0.024**	0.016*		0.014
		(0.007)	(0.007)	(0.007)	(0.009)		(0.009)
Leverage		-0.024	-0.003	-0.024*	-0.028		0.017
		(0.017)	(0.019)	(0.014)	(0.022)		(0.027)
R^2	0.252	0.320	0.138	0.320	0.387		0.451
N	145	143	143	143	136		143
Sector F.E.	yes	yes	no	yes	yes	no	yes
Adjusted S.E.	no	no	no	yes	no	no	no
Weights	no	no	no	no	yes	no	no
Matching E'tor	no	no	no	no	no	yes	no

Notes: Ordinary Least Squares estimates of specification (1) for the event window January 25 to March 30, 2011

$$CR[n, m] = N_i'\gamma + X_i'\nu + \eta_s + \epsilon_i.$$

The dependent variable in columns 1-6 is $CR[n, m]$, the cumulative return on each firm's stock between the opening of trade on the start date n and the closing of trade on the end date m. Columns 7 instead uses the cumulative abnormal return relative to an Egyptian market CAPM, $CAR[n, m]$, as dependent variable. N_i denotes the vector of dummies reflecting NDP-, military-, and Islamic-connected firms. The vector of controls, X_i, contains a constant term, each firm's world-market beta, β_i^{World}, Egyptian-market beta, β_i^{Egypt}, unrest beta, β_i^{Unrest}, and controls for size and leverage. η_s denotes a full set of (16) sector fixed effects. Robust standard errors are in parentheses. In column 5, each observation is weighted with the log number of transactions on the last trading day of the event window. Standard errors in column 4 are adjusted for the cross-correlation of firms' returns in pre-event data. Columns 6 uses a synthetic matching estimators calculated from comparing the returns on 20 NDP-, 32 military-, and 13 Islamic-connected firms with 97 non-connected firms. 95% confidence intervals are in brackets.

Table 3: Post-Mubarak Events

	(1)	(2)	(3)	(4)
Panel A	Events during Military Rule			
	Military Crackdown	Retake Tahrir	Presidential Elections 1st round	2nd round
	CR[91,117]	*CR[163,165]*	*CR[291,292]*	*CR[309,310]*
NDP	0.004	-0.010	-0.015	0.018**
	(0.029)	(0.012)	(0.010)	(0.008)
Military	0.080*	-0.024**	0.002	0.015*
	(0.044)	(0.008)	(0.007)	(0.009)
Islamic	-0.009	0.001	0.010	0.022*
	(0.030)	(0.012)	(0.008)	(0.012)
R^2	0.025	0.250	0.068	0.241
N	138	141	126	137
Panel B	Events during Islamist Rule			
	Generals sacked	Constitution passes	Mursi sacked	
	CR[343,344]	*CR[433,433]*	*CR[541,562]*	
NDP	-0.002	-0.011**	-0.019	
	(0.006)	(0.005)	(0.021)	
Military	-0.004	0.003	-0.009	
	(0.007)	(0.005)	(0.029)	
Islamic	0.010*	-0.005	-0.054**	
	(0.006)	(0.005)	(0.016)	
R^2	0.069	0.050	0.054	
N	122	128	127	
Sector F.E.	yes	yes	yes	yes
Std. Controls	yes	yes	yes	yes

Notes: Ordinary Least Squares estimates of specification (1):

$$CR[n,m] = N_i'\gamma + X_i'\nu + \eta_s + \epsilon_i.$$

Dependent variable in all columns is $CR[n,m]$, the cumulative return on each firm's stock between the opening of trade on the start date n and the closing of trade on the end date m. N_i denotes the vector of dummies reflecting NDP-, military-, and Islamic-connected firms. X_i, contains a constant term, each firm's world- and Egyptian market beta, unrest beta, and controls for size and leverage. η_s denotes a full set of (16) sector fixed effects. Robust standard errors in parentheses. Event windows are as followPanel A: event windows are July 31-September 08, 2011 (column 1), November 12-21, 2011 (column 2), May 28-29, 2012 (column 3), and June 24-25, 2012 (column 4). Panel B: event windows are August 12-13, 2012 (column 1), December 23-23, 2012 (column 2), and June 4-July 4, 2013 (column 3).

Table 4: Pooled Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Daily Log Returns × 100					
Incumbent x Event	-0.340***	-0.423***	-0.402***	-0.461***	-0.520***	-0.368***
	(0.093)	(0.090)	(0.089)	(0.091)	(0.099)	(0.109)
Other Connected x Event	0.107	0.087	0.093	0.072	0.028	0.077
	(0.068)	(0.075)	(0.076)	(0.077)	(0.080)	(0.075)
R^2	0.386	0.404	0.404	0.404	0.404	0.405
N	78705	78705	78705	78705	78705	78705
$p-val$(Equal w/Opp. Sign)	0.062	0.008	0.015	0.003	0.001	0.036
$p-val$(Equal w/Opp. Sign), Weighted	0.360	0.120	0.170	0.059	0.016	0.197
Include time effect $\times X_i$	no	yes	yes	yes	yes	no
Include firm fixed effect	no	no	yes	no	no	no
Include time effect $\times X_i^2$	no	no	no	yes	no	no
Include sector effect × Event	no	no	no	no	yes	no
Include time effect × sector effect	no	no	no	no	no	yes

Notes: Ordinary Least Squares estimates of specification

$$R_{it} = I_{it}\ \gamma + (E_t \times I'_{it})\ \gamma^p + X'_i \nu_t + \delta_t + \eta_s + \epsilon_{it}.$$

Dependent variable in all columns is R_{it}, the log return on firm i at time t multiplied by 100. I_{it} denotes a vector of two dummies reflecting connections to the incumbent government and to the two other non-incumbent power groups during each of the four phases of Egypt's Arab Spring, respectively. Event (E_t) denotes a variable takes values of $\{+1, -1, 0\}$ on all event days from Tables 2 and 3, denoting the event at time t to be {bad, good, neutral} for the incumbent, where the events are classified as follows: Mubarak's Fall (+1), Military Crackdown (-1), Retake Tahrir (+1), 1st round (0), 2nd round (+1), Generals sacked (-1), Constitution passes (-1), and Mursi sacked (+1). E_t is also 0 on days without events. X_i denotes the vector of controls that contains β_i^{World}, β_i^{Egypt}, β_i^{Unrest}, and controls for firm-size and leverage. δ_t and η_s are time and sector fixed effects, respectively. Robust standard errors are in parentheses. Column 3 adds firm fixed effects to the baseline specification in column 2. Column 4 includes the interaction of time effects and the square of all entries in X_i. Column 6 includes the interaction of the sector effects with E_t. Column 7 includes the interaction of all (16) sector fixed effects with the time effects. The first set of p-values reported is for tests of the hypothesis that the two reported ceofficients are equal with opposite sign. The second set of p-values repeats the same tests but weights each coefficient with the average market cap of incumbent and other connected firms in the sample, respectively.

Table 5: External Validity

	(1)	(2)	(3)
Panel A		Number of Board Members	
	Pre-Revolution	Military Rule	Islamist Rule
	Jan 1, 2011	*Jun 30, 2012*	*Jun 30, 2013*
Prominent NDP members	19	16	14
Using military titles	21	28	22
Known Muslim Brothers	1	0	0
Panel B		Profitability of Connected and Non-connected Firms	
	Pre-Revolution	Military Rule	Islamist Rule
	Jul 2009-Jun 2010	*Jul 2011-Jun 2012*	*Jul 2012-Jun 2013*
NDP-connected firms	0.045**	-0.008	-0.091*
	(0.023)	(0.020)	(0.047)
Military-connected firms	0.01	0.074	-0.118
	(0.048)	(0.060)	(0.147)
Islamic firms	-0.014	-0.012	-0.018
	(0.029)	(0.030)	(0.034)
Intercept (Non-connected firms)	0.070***	0.040***	0.119***
	(0.012)	(0.011)	(0.046)

Notes: Panel A shows the total number of board members of firms in our sample who appear on a list of 6,000 prominent NDP members, who use military titles, or who are known Muslim Brothers (see section 2 of the main text for details). Panel B shows results of three regressions (for each accounting year) of firm-level profitability on a dummy for NDP, Military, and Islamic-connected firms. Note that the reporting years 2012 and 2013 coincide roughly with our definition of the "Military Rule" and "Islamist Rule" periods as defined in Table 1. Profitability is calculated as net profit after taxes divided by total shareholder equity. Robust standard errors are in parentheses.

Table 6: The Effect of Street Protests on Stock Market Valuations

	(1)	(2)	(3)	(4)
	Mubarak's Fall	Military Rule	Islamist Rule	Post-Islamist
	Daily Log Returns × 100			
NDP x Tahrir Protesters	-1.614***	-0.135	0.672*	-0.308
	(0.602)	(0.411)	(0.382)	(0.742)
Military x Tahrir Protesters	-0.886	-0.889***	-0.527	-0.145
	(0.612)	(0.326)	(0.324)	(0.617)
Islamic x Tahrir Protesters	1.773	0.600	0.421	-1.332*
	(1.213)	(0.382)	(0.477)	(0.815)
NDP x Rabaa Protesters				-8.089
				(11.595)
Military x Rabaa Protesters				-6.406
				(9.539)
Islamic x Rabaa Protesters				27.850**
				(12.895)
R^2	0.610	0.331	0.421	0.423
N	5603	43997	27210	1895
Total # Tahrir Protesters	1.220	5.290	4.175	1.020
Total # Rabaa Protesters				0.206
Incumbent	NDP	Military	Islamic	Islamic

Notes: Ordinary Least Squares estimates of specification (2),

$$R_{it} = N_i\gamma + \left(P_t \times N_i'\right)\gamma^p + X_i'\nu_t + \delta_t + \eta_s + \epsilon_{it},$$

for each of the four phases of Egypt's Arab Spring. Dependent variable in all columns is R_{it}, the log return on firm i at time t multiplied by 100. N_i denotes the vector of dummies reflecting NDP-connected, military-connected, and Islamic firms. P_t denotes the number of protesters in Tahrir Square, capped at and normalized with 500,000. X_i denotes the vector of controls that contains β_i^{World}, β_i^{Egypt}, β_i^{Unrest}, and controls for firm size and leverage. δ_t and η_s are time and sector fixed effects, respectively. The specification in column 4 also contains the interaction between N_i and the number of (pro-Islamist) protesters in Rabaa Square. Total # Protesters gives the sum of our (capped and normalized) measure of Tahrir and Rabaa protesters by phase. Robust standard errors are in parentheses.

Table 7: Protests Reduce Stock Market Valuation of Firms Connected to Incumbent Government

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Daily Log Returns $\times$ *100*								
Incumbent x Tahrir Protesters	-0.879***	-0.751***	-0.834***	-0.855***	-0.754***	-0.695***	-0.483*	-0.685***	-0.548**
	(0.243)	(0.254)	(0.278)	(0.281)	(0.255)	(0.252)	(0.247)	(0.234)	(0.271)
Other Connected x Tahrir Prot.	-0.281	-0.160	-0.110	-0.122	-0.165	-0.092	-0.008	-0.166	-0.243
	(0.205)	(0.216)	(0.227)	(0.228)	(0.218)	(0.217)	(0.222)	(0.208)	(0.223)
R^2	0.386	0.404	0.337	0.320	0.404	0.404	0.405	0.387	0.404
N	78705	78705	72527	66857	78705	78705	78705	78705	78705
$p-val$ (Equal w/ Opp. Sign)	0.001	0.010	0.014	0.011	0.010	0.029	0.187	0.013	0.026
$p-val$ (Equal w/ Opp. Sign), Weighted	0.003	0.034	0.053	0.043	0.033	0.083	0.332	0.038	0.043
Include time effect $\times X_i$	no	yes	yes	yes	yes	yes	yes	no	no
Drop changes in gov't or constitution	no	no	yes	yes	no	no	no	no	no
Drop all events analyzed in section 3	no	no	no	yes	no	no	no	no	no
Include firm fixed effect	no	no	no	no	yes	no	no	no	no
Include time effect $\times X_i^2$	no	no	no	no	no	yes	no	no	no
Include sector effect $\times$ Tahrir Protesters	no	no	no	no	no	no	yes	yes	no
Include time effect $\times$ sector effect	no	no	no	no	no	no	no	no	yes

Notes: Ordinary Least Squares estimates of specification

$$R_{it} = I_{it}\,\gamma + (P_t \times I'_{it})\,\gamma^p + X'_i\nu_t + \delta_t + \eta_s + \epsilon_{it}.$$

Dependent variable in all columns is R_{it}, the log return on firm i at time t multiplied by 100. I_{it} denotes a vector of two dummies reflecting connections to the incumbent government and to the two other non-incumbent power groups during each of the four phases of Egypt's Arab Spring, respectively. P_t denotes the number of protesters in Tahrir Square, capped at and normalized with 500,000. X_i denotes the vector of controls that contains β_i^{World}, β_i^{Egypt}, β_i^{Unrest}, and controls for firm-size and leverage. δ_t and η_s are time and sector fixed effects, respectively. All specifications also control for the interaction between I_{it} and the number of (pro-Islamist) protesters in Rabaa Square. Robust standard errors are in parentheses. Column 2 shows our baseline specification. Column 3 drops all dates identified in our event analysis as involving changes in government or formal institutions plus the next three trading days (in particular, it drops the fall of Mubarak, the first and the second round of presidential elections, the passing of the Muslim Brotherhood's constitution, and the military coup against Mursi). In column 4, we drop all of the events studied in Tables 2 and 3 plus three trading days after each event. Column 5 adds firm fixed effects to the baseline specification in column 2. Column 6 includes the interaction of the number of protesters in Tahrir square square of the parametric controls in the vector X_i. Column 7 includes the interaction of all (16) sector fixed effects with the number of protesters in Tahrir Square, $P_t \times \delta_s$. Column 8 shows the same specification as column 7 but drops the interaction $\delta_t \times X_i$. Column 9 also drops the interaction $\delta_t \times X_i$, but includes the interaction of time fixed effects with sector fixed effects, $\delta_t \times \delta_s$. The first set of p-values reported is for tests of the hypothesis that the two reported ceofficients are equal with opposite sign. The second set of p-values repeats the same tests but weights each coefficient with the average market cap of incumbent and other connected firms in the sample, respectively.

Table 8: Timing of the Effect & Interactions of Protests with a Measure of Past Rents

	(1)	(2)	(3)	(4)
Panel A	Timing of the Effect of Protests on Market Valuation of Connected Firms			
	Daily Log Returns × 100			
Incumbent x Tahrir Protesters		-0.757***	-0.736***	-0.751***
		(0.254)	(0.255)	(0.256)
Other Connected x Tahrir Protesters		-0.143	-0.153	-0.146
		(0.218)	(0.217)	(0.218)
Lead Incumbent x Tahrir Prot.	0.003	0.063		
	(0.250)	(0.254)		
Lead Other Connected x Tahrir Prot.	-0.099	-0.071		
	(0.224)	(0.228)		
Lag 1 Incumbent x Tahrir Prot.			-1.522***	-1.501***
			(0.347)	(0.348)
Lag 1 Oth. Connected x T. Prot.			0.465	0.464
			(0.336)	(0.336)
Lag 2 Incumbent x Tahrir Prot.				-0.580*
				(0.349)
Lag 2 Oth. Connected x T. Prot.				0.010
				(0.288)
Lag 3 Incumbent x Tahrir Prot.				-0.143
				(0.263)
Lag 3 Oth. Connected x T. Prot.				0.114
				(0.240)
R^2	0.404	0.404	0.404	0.404
N	78705	78705	78705	78705
Panel B	Interaction of Protests with a Measure of Past Rents			
	Daily Log Returns × 100			
Incumbent x Tahrir Protesters	-0.859***	-0.732***	-0.670***	-0.534*
	(0.244)	(0.254)	(0.236)	(0.273)
Incumbent x Tahrir Prot. x Rent 2010	-20.282***	-12.234	-19.190***	-12.117*
	(7.570)	(10.459)	(6.344)	(7.327)
R^2	0.386	0.404	0.387	0.404
N	78705	78705	78705	78705
Include time effect $\times X_i$	no	yes	no	no
Include sector effect × Tahrir Protesters	no	no	yes	no
Include time effect × sector effect	no	no	no	yes

Notes: Panel A shows variations of the baseline specification in column 2 of Table 7 that add leads and lags of the term $(P_t \times I'_{it})$, where I_{it} again denotes the vector of two dummies reflecting affiliation to the incumbent government and to the two other non-incumbent power groups during each of the four phases of Egypt's Arab Spring. See the caption of Table 7 for details. The specification in column 1 adds leads while dropping the interaction of the current number of protesters with I_{it}. Panel B shows variations of the specifications in column 1, 2, 8, and 9 of Table 7, respectively, that add the triple-interaction of I_{it}, the number of protesters in Tahrir square (capped and normalized in the same way as in Table 7), and "Rent 2010" measured as the ratio of bank loans over total assets in the 2010 accounting year.

Table 9: Activity on Twitter Predicts Protests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mubarak's Fall	Military Rule	Islamist Rule	Post-Islamist	All Phases			
Panel A	*Number of Tahrir Protesters*							
Tahrir Hashtags	3.834**	0.089***	0.642**	0.707	0.219***		0.108	0.237*
	(1.922)	(0.025)	(0.261)	(0.738)	(0.075)		(0.115)	(0.133)
Lag Tahrir Hashtags						0.225***	0.137	
						(0.077)	(0.123)	
Lead Tahrir Hashtags								-0.022
								(0.117)
Internet Shutdown	2.006*				1.859*	1.865*	1.871*	1.858*
	(1.090)				(1.069)	(1.070)	(1.070)	(1.070)
R^2	0.148	0.046	0.250	0.112	0.078	0.080	0.083	0.077
N	83	483	326	25	917	917	917	916
Panel B	*Number of Tahrir Protesters*							
Retweets of Opp.	-1.037	0.047***	0.469***	0.035	0.258**		0.181	0.137
	(1.265)	(0.018)	(0.123)	(0.063)	(0.103)		(0.136)	(0.195)
Lag Retweets of Opp.						0.240***	0.098	
						(0.091)	(0.102)	
Lead Retweets of Opp.								0.155
								(0.151)
Internet Shutdown	1.232				1.987*	1.974*	2.005*	2.016*
	(1.076)				(1.074)	(1.074)	(1.075)	(1.073)
R^2	0.021	0.002	0.370	-0.043	0.095	0.087	0.098	0.104
N	83	483	326	25	917	917	917	916
Panel C	*Number of Tahrir Protesters*							
Tahrir Hashtags					0.140***		0.080	0.174*
					(0.050)		(0.107)	(0.101)
Lag Tahrir Hashtags						0.155**	0.079	
						(0.061)	(0.120)	
Lead Tahrir Hashtags								-0.055
								(0.104)
Retweets of Opp.					0.202*		0.133	0.086
					(0.107)		(0.138)	(0.198)
Lag Retweets of Opp.						0.178*	0.081	
						(0.092)	(0.107)	
Lead Retweets of Opp.								0.151
								(0.159)
Internet Shutdown					1.993*	1.984*	2.012*	2.018*
					(1.074)	(1.074)	(1.076)	(1.074)
R^2					0.111	0.106	0.116	0.117
N					917	917	917	916

Notes: Ordinary Least Squares estimates with robust standard errors in parentheses. Dependent variable in all columns is the number of protesters in Tahrir Square on any given day. Independent variables are the number of tweets with Tahrir hashtags (Panels A and B) and the number of retweets received by opposition leaders (Panels B and C). The dependent variable and these independent variables are normalized by deducting the sample mean and dividing by the sample standard deviation. All specifications contain a constant term (not reported) and a fixed effect for days in which Twitter was blocked in Egypt (Internet Shutdown, not reported in Panel C).

Table 10: Activity on Twitter and Stock Returns

	(1)	(2)	(3)	(4)	(5)
			Daily Log Returns $\times$ *100*		
Incumbent x Tahrir Protesters		-0.072***		-0.084***	-1.548*
		(0.023)		(0.023)	(0.805)
Other Connected x Tahrir Prot.		-0.003		-0.004	0.396
		(0.026)		(0.026)	(0.548)
Incumbent x Tahrir Hashtags	0.015	0.023			
	(0.025)	(0.026)			
Other Connected x T. Hashtags	-0.018	-0.018			
	(0.024)	(0.025)			
Incumbent x Retweets of Opposition			0.050*	0.060**	
			(0.029)	(0.030)	
Other Connected x Retweets of Opp.			-0.013	-0.015	
			(0.023)	(0.025)	
Incumbent x Opposition Turnover					-0.003
					(0.007)
Connected x Opposition Turnover					-0.001
					(0.006)
Incumbent x Tahrir Prot. x Opp. Turnover					0.138*
					(0.075)
Other Connected x T. Prot. x Opp. Turnover					-0.037
					(0.051)
R^2	0.404	0.404	0.404	0.404	0.404
N	78705	78705	78705	78705	78705

Notes: Ordinary Least Squares estimates of specification,

$$R_{it} = I_{it}\gamma + \left(P_t \times I_i'\right)\gamma^p + \left(T_t \times I_i'\right)\gamma^T + X_i'\nu_t + \delta_t + \eta_s + \epsilon_{it}.$$

Dependent variable in all columns is R_{it}, the log return on firm i at time t multiplied by 100. I_{it} denotes the vector of two dummies reflecting affiliation to the incumbent government and to the two other non-incumbent power groups, respectively. P_t denotes the number of protesters in Tahrir Square. T_t denotes measures of activity on Twitter (Tahrir Hashtags and Retweets of Opposition). T_t and P_t are normalized by deducting the sample mean and dividing by the sample variance. X_i denotes the vector of controls that contains β_i^{World}, β_i^{Egypt}, β_i^{Unrest}, and controls for firm size and leverage. δ_t and η_s are time and sector fixed effects, respectively. Robust standard errors are in parentheses. Column 5 adds the triple-interaction $I_t \times P_t \times O_t$ where O_t is the opposition turnover rate measured as the number Twitter users who re-tweet a tweet of an opposition leader in $t-1$ but not in t, divided by the average number of re-tweeters on the two days in percent.

Appendix – For Online Publication

A Appendix to Section 2

A.1 Construction of Unrest Beta

This appendix describes the procedure for generating a time series of violent disruptions in Egypt from 2005 through 2010. We use the Global Data on Events, Location, and Tone (GDELT) dataset that contains nearly a quarter-billion political events that occurred across the world from 1979 to the present. An event is defined as an action taken by a national, subnational, or transnational actor upon another such actor. Every event and actor is coded using the Conflict and Mediation Event Observations (CAMEO) coding system. These events are extracted from news reports by the Textual Analysis by Augmented Replacement Instructions (TABARI) software with a few additional modifications specific to GDELT for information on location and tone. News sources include international, regional, and local news sources, all either in English or translated to English so that TABARI can parse the reports.

GDELT uses TABARI to analyze every sentence in a news report, although TABARI ordinarily only analyzes the lead sentence. TABARI uses simple grammatical rules of the English language to parse one sentence at a time and identify the subject, verb phrase, and direct object. The subject and object are then checked against a dictionary of 60000 political, religious, and ethnic actors (i.e., proper nouns) and 1500 agents (i.e., common nouns). If the subject or object is found in the dictionary, then it is converted into a sequence of CAMEO actor codes using the dictionaries; otherwise, the sentence is ignored. For example, the dictionary would map "Egyptian President Hosni Mubarak" to "EGYGOV" (Egyptian government). The subject who initiates the action is called the source, and the object who receives the action is called the target. Not all event records in GDELT have both a source and a target. The verb phrase is similarly checked against a dictionary of verb phrases and either converted to a CAMEO event code or ignored. The location of an actor or verb is defined as the geographic location in the text of the article that is the fewest words away from that actor or verb. For example, if "Cairo" is five words away from the source actor "Mubarak" and "Israel" is twelve words away from "Mubarak", then Cairo will be selected as Mubarak's location. Any event records with exactly the same date, source, target, and event codes are collapsed into a single event record.

We run five Python scripts as follows. The first script downloads files from the GDELT server a chunk at a time, stores them in our directory, and unzips the packages. We download all GDELT files from 2005 to March 2013. The second script looks at every datapoint in the subset of GDELT downloaded by the first script, checks if the event is somehow recorded as being located in Egypt and if the event is coded as 14 (protest), 18 (assault), or 19 (fight). If the event satisfies these two conditions, then the script stores its two actor codes into a list. The list of unique actor codes is then written to a separate file. This file is then manually edited into another file (we refer to this edited list as the actor sublist), so that it contains only Egyptian actors, relevant transnational actors (e.g., most UN organizations, IMF, multinational corporations), relevant ethnic actors (e.g., Arabs), relevant religious actors (e.g., Christians, Muslims), and all subnational actors (e.g., police, government, media, health, criminals, rebels, insurgents). The third script creates two time series, one for events under the 143 event code (strikes and boycotts) and one for events under the 145 event code (protest violently, riot). It creates these time series by filtering all GDELT data downloaded by the first script for events that (1) are somehow recorded as being located in Egypt, and in which (2) both actors are members of the actor sublist, and (3) the event base code is 143 for one time series and 145 for the other time series. It records all events that pass these filters into two time series to separate files. The fourth script creates a time series of violence involving Copts by filtering the subset of GDELT. The conditions for the filter are (1) either one of the actors is recorded as Coptic or one of the actors is both Christian and Egyptian and the event is somehow recorded as being located in Egypt, and (2) the event code is either 14 (protest), 18 (assault), 19 (fight), or 20 (mass violence). The fifth script splits the three time series above into bunchings so that each bunching can be manually verified, where a bunching is defined as a series of events such that no two consecutive events in the series are more than five days apart. This script also adds two new columns to each time series. The columns "strike" and "strike verified" are added to the 143 time series; "riot" and "riot verified" are added to the 145 time series; "copts" and "copts verified" are added to the Copts time series. The former of the two columns is recorded as 1 for every datapoint. The latter is recorded as 0 for every datapoint, to be changed to 1 if the event is verified.

Then, we manually verify each bunching in the three time series by checking each bunching to see if corresponds to an event recorded in one of the Major World Publications on LexisNexis. After performing this LexisNexis search, we look through the search results for an event that could be classified as either 143, 145, or violence involving Copts. If such an event is found, we verified the entire bunching by changing the 143/145/copts verified variable to 1 for all events in that bunching. If the bunching is long (almost a month or longer), then we do not verify all datapoints in the bunching; instead, we define an interval by the publication date of the chronologically first such article that fits the time series and the date of the last such article that fits the time series and verified all datapoints in that interval (which is a subset of the interval spanned by the bunching).

A.2 Classification of Firms

In this appendix we explain the procedures of classifying our firms as connected to the NDP or the Military.

A.2.1 NDP-Connected Firms

To classify firms as connected to the NDP, we first scrape a list of names from the website emeskflol.com. This is a list of approximately 6,000 prominent NDP members posted online by activists in the aftermath of the fall of the Mubarak regime. The list was created as part of an internet campaign called "Emsek Felool" ("to catch remnants" of the old regime) in order to identify publicly the cronies of the old regime. The list gives the full name, the rank within the NDP, and any official function of each prominent NDP member by Egyptian governorate. The functions it lists include members of parliament, aldermen, and local and party council members. We classify a firm as connected to the NDP if the name of at least one of the firm's major shareholders or board members appears on the felool list.

We implement the following merge procedures. If the board member (or the shareholder) name consists of two names (first and last name), we apply the following criteria: 1) do the person listed in the felool list and the person listed as a board member (or shareholder) have the same last name? If yes, 2) do the person on the felool list and the person listed as a board member (or shareholder) have the same first name? If yes, then we consider the person on the felool list and the board member (or the shareholder) as potentially the same person. If the board member (or the shareholder) name consists of more than two names, we apply the following four criteria: 1) do the person listed on the felool list and the person listed as a board member (or shareholder) have the same last name? If yes, 2) do the person on the felool list and the person listed as a board member (or shareholder) have the same first name? If yes, 3) do the person on the felool list and the person listed as a board member (or shareholder) share a first letter of any of the middle names? If yes, 4) do the person on the felool list and the person listed as a board member (or shareholder) share at least one letter of any of the middle names? If yes, then then we consider the felool person and the board member (or the shareholder) as potentially the same person. We then manually review all the potential matches generated by the above merging procedures.

A.2.2 Military-Connected Firms

In accordance with the Egyptian constitution, the Egyptian military's financial accounts are outside the control of the civilian government (the "two tills" system). We classify listed firms as connected to the Egyptian military if they are wholly or partially owned by the military "till". We identify these firms first by selecting all state-owned holding companies, that is, government-owned entities that hold stock in listed firms, from the Zawya database. Although these holdings do not officially declare which of the two "tills" they are accountable to, we distinguish between military- and civilian-government owned holdings simply by checking whether the principal officers, shareholders, or board members of the holding company (or any of its affiliated firms) are linked to the military. Appendix Table 14 lists these entities, their link to the military and the sources that document these links.

A.3 Protester Data

We run several Python scripts to construct our time series of the number of protesters. Three main scripts fully describe this process. The first extracts the number of protesters for each article, the second extracts the date of the protest from each article, and the third edits the data. We describe each of these scripts in detail in a separate subsection below. The final output is a table in which each date has a single row and each newspaper has a single column. An entry in this two-dimensional grid is the maximum observation reported by that newspaper on that date.

A.3.1 Retrieving the Newspaper Articles

Starting from January 25, 2011, through the end of July 2013, we download all newspaper articles containing the words "protesters"/"protestors", "Tahrir" and "Egypt" from newspapers in the category "major world publications" of the Lexis Nexis Academic Service and from all English-language Egyptian news outlets that are available on the service (Al-Ahram Gate, Al-Ahram Weekly, Al-Akhbar English, and Daily News Egypt). We write a script that downloads for each article, its news source, date of publication, and the text of the article. After searching for these articles, they are downloaded in sets of 500 articles (since LexisNexis caps downloads at 500 articles, and caps searches at 3000) in plain text (.txt) format. In order to ensure that the Egyptian press covered by our analysis is balanced between pro- and anti-regime news outlets, we supplement the pool of articles downloaded from LexisNexis with the online content of three Egyptian news outlets: Al-Masry Al-Youm (http://www.egyptindependent.com/), Al-Ahram English (http://english.ahram.org.eg/), and Copts United (http://www.copts-united.com/English/). These three newspapers are chosen because (1) their web sites are coded in a manner that made it possible to scrape with Python, and (2) the web sites offer coverage going back to January 25, 2011. Although each news source has its own script to scrape articles, the procedure of each is roughly the same. The script looks at the pre-filtered list of top news stories. It extracts the URL for each story and possibly the date of publication. It then goes to each URL and extracts the text of the article and the date of publication if not yet extracted. The script then goes to the next page of top stories and repeats. For Copts United in particular, the lists of top stories are not paginated like the other news sources. For Copts United, each top story has a particular index, and the list of top stories when that index is fed into the URL is that top story and the ten or so other top stories following it. Therefore, the Copts United scraper only extracts a single URL from each list of top stories (i.e., the URL of the top story with that particular index), goes to that URL, and extracts the article text. It then repeats this process for the next index.

A.3.2 Identifying the Number of Protesters

The purpose of this script is to extract the number of protesters from the articles that we collected. The script first checks to make sure that the words "protestors"/"protesters", "Tahrir" and "Egypt" are indeed in the article. It then cuts text snippets (with a length of 61 words) surrounding numbers (including numbers like "more than a thousand" or "over a hundred thousand"), and filters these text snippets to increase the chance that these numbers are indeed the number of protesters in Tahrir Square. Specifically, there are eight sub-filters in the filter: (1) Checks that there is a synonym of "protester" in the text snippet, (2) Checks that there is a synonym of "Tahrir Square" in the text snippet, (3) Checks that the word following the number is not an irrelevant word, i.e., a word that indicates that the snippet does not contain the number of protesters, e.g., "mile", "killed", "soldiers", "videos", "gmt", (4) Checks that the number is not a year, ranging from 1901 to 2014, with year 2000 excluded, (5) Checks that the number is not too small, i.e., less than 100, (6) Checks that words in a tighter radius (seven words) around the number are not irrelevant words, e.g., "arrested", "Alexandria", "pro-regime", "population", "Qaddafi", (7) Checks that irrelevant (e.g., "Syria", “Baghdad”, “Boston”) are not anywhere in the snippet, and (8) Checks that specifically pro-MB words (e.g., “pro-Morsi”, “pro-Mursy”, “pro-Brotherhood”, “Brotherhood supporters”) are not anywhere in the snippet if the article was published after the constitutional referendum (on March 19, 2011). Once the script has a list of text snippets for each article, it chooses the maximum number among each article’s text snippets. It takes the maximum number rather than all numbers because many newspapers report the total number of protesters in Tahrir Square that day, as well as subsets who, e.g., marched to the presidential palace; choosing only the maximum prevents a downward bias caused by observations that are only of subsets of the protest, not the total protest.

A.3.3 Identifying the Date of the Protest

This script looks for a date near the number of protesters and also the first date that appears in the article, using a relative date word, like “yesterday”, “last night”, or “Tuesday”. If there are one or more dates near the number of protesters, it chooses the one closest to the number of protesters. If there is no date near the number of protesters, it chooses the first date in the article as the date of the protest. It then determines the calendar date by subtracting the right number of days from the date of publication. For example, if the chosen date is “yesterday”, then the date of the protest will be the date of publication minus one day. If the chosen date is “Tuesday”, it checks if the date of publication is on a Tuesday, in which case it decides that the protest date is the publication date, and if not, then it uses the last Tuesday before the publication date as the protest date. If it cannot find any date in the article, it marks the date as missing data.

A.3.4 Editing the Data

Our final script converts numbers written as words into numbers, e.g., “one hundred” into 100, “few thousand” into 5000, “several thousand” into 5000, etc. (For a more detailed listing of this mapping see Appendix Table 15.) It then adds an observation for days in which no newspaper reported a protest in Tahrir; this observation has 0 protesters, and the news source, publication date, and article text are marked as missing data.

A.4 Classification of Opposition Figures

We define the opposition during a given phase of the Arab Spring as a group of prominent Twitter users asking protesters to gather in Tahrir to demand the removal of the incumbent government. To this end, we classify prominent Twitter users listed in Appendix Table 16 into four camps: Secular, Muslim Brotherhood (MB), Salafist, and Old Regime (that is, both NDP and Military). We search official sources on the internet for public announcements made by each of the above groups regarding their intention to join Tahrir protests. Then, our choice of which political groups constitute the opposition in a given phase is defined on the basis of these public announcements. For instance, the MB’s political wing, the Freedom and Justice Party, announced their refusal to take part in the demonstrations that aimed to put an end to the Military rule. So, while Twitter accounts of Muslim Brotherhood activists are included in our definition of opposition during the Fall of Mubarak (phase 1), they are excluded during the period of Military Rule (phase 2). In July 2013, following the military coup against President Morsi, members of April 6th group participated in The Third Square, a movement that rejects both MB and military rule. So, while the April 6th members are included in phases 1, 2, and 3, they are excluded from phase 4. We end up with the following classification of opposition: Phase 1 (Mubarak's Fall): Secular, MB, Salafist; Phase 2 (Military Rule): Secular; Phase 3 (Islamist Rule): Secular and Old Regime supporters (NDP and Military); Phase 4 (Post-Islamist): Secular, Salafist, and Old Regime supporters (NDP and Military).

A.5 Twitter Data

In this appendix we describe how we assemble our databases of Egyptian tweets. To build our Twitter databases we use a number of scripts that each serve a different function. We first describe the general ideas behind the scraping process and how the data are assembled and then we describe our two main Twitter databases.

A.5.1 The Twitter Scripts

We use the Twitter Application Programming Interface (API) to scrape our data. The Twitter API is a tool used to access data available from Twitter. It allows authorized applications to interface with Twitter's data. We use the REST API version as it allows access to historical tweets. Twitter uses the OAuth authentication protocol to allow access to the API. In order to access the API, we first create a Twitter developer account and then get the access keys for this account. This allows us to make requests to the Twitter API. There are several types of requests that we made to the API. The first type requests the timeline of a user. To do this, we specify the screen name or Twitter ID for the user in question. The timeline is a list of all available tweets for the given user. Twitter puts a limit on the number of tweets returned by this method. We can get a maximum of the most recent 3200 tweets with a "get timeline" request. The second type of request gets the retweets for a given tweet. A request to get retweets will return the 100 most recent retweets for the given tweet. The tweet can be specified with a tweet ID, which is included in the tweet object. The two types of requests return a list of tweet objects. A tweet object is one of the basic units available from the Twitter API. It contains a large amount of information on the tweet and the user who made the tweet. (The full list is available at https://dev.twitter.com/docs/platform-objects/tweets.) The first key element is the text. The text contains the actual text of the tweet. This is in unicode, allowing for non-Latin characters. The text is limited by Twitter's policy to 140 characters. The tweet also contains a created-at element which represents when the tweet was published by the user. This is a UTC time stamp. We primarily limit ourselves to days, however, the time stamp allows for more granular units of measurement. The tweet also contains an internal ID that can be used to get other information about the tweet, including retweets.

To scrape the Twitter data, we run a Python script that downloads the desired data and stores the resulting tweets in json files. These json files are later moved into a MongoDb database to make access easier.

A.5.2 The Twitter Databases

Our Twitter analyses are based on the combination of two databases. The first database covers all the tweets for a list of roughly 318 thousand Egyptian users who tweeted at least once between July 1, 2013 and September 17, 2013. We obtain this list from an Egyptian social media firm (25trends.me). We implemented the following procedure to obtain the tweets of these users. For each of these users, we had a screen name and were able to get the tweets using the "get timeline" request mentioned above. Due to the limitations of the "get timeline" request, this database only has the most recent 3200 tweets for each user. While this means that for the majority of users we have their entire timeline of tweets, there are a number of cases where the user had too many tweets to get the entire timeline. 262442 users have less than 3200 tweets (i.e., 82.4% of our list of Egyptian users). The resulting database contains 311302456 tweets made during our sample period, from January 1, 2011 through July 29, 2013. 71807168 of these 311 million tweets are retweets of other users' tweets.

The second database covers all the retweets of the tweets by Egyptian users identified by Socialbakers (http://www.socialbakers.com/twitter/country/egypt/)as the most prominent users. It consists of retweets of a central list of roughly 620 Social Bakers users. A Social Bakers user is an Egyptian Twitter user who Social Bakers identified as socially or politically important. We extract the reweets of these 620 users from the reweets included in our first database explained above. There are two ways to identify a retweet. First, the retweet tweet object will in some cases contain an identifier indicating that the tweet is a retweet. This is a more recent feature of tweets and is only active in some cases. A more consistent method of finding retweets is to identify tweets that start with "RT". This is the standard syntax for starting a retweet on Twitter.[32]

B Appendix to Section 3

B.1 Adjusted standard errors

To adjust for the possibility that other factors cause correlation in the error term ϵ_i across firms, we estimate adjusted standard errors that account for potential cross-firm correlation of residual returns. We estimate the cross-correlation matrix of residual returns using pre-event return data on a window between January 1 and December 23, 2010. For each day during this interval we estimate (1), holding constant the length of the event measured in trading days $(m - n + 1)$. This estimated cross-correlation matrix is then used to calculate our standard errors, under the assumption that the pre-event cross-correlation matrix is an appropriate estimate of the cross-correlation matrix during the event. To calculate the variance-covariance matrix of residuals we then scale the cross-correlation matrix with the mean squared error of residuals obtained from the actual event window. We use this scaling to correct for the fact that any missing observations (stocks that do not trade on a given day) would otherwise yield a downwardly biased estimate of the volatility of residuals.

[32] We supplement our retweet database with another retweet database that we complied at the beginning of this project. This database consists of the retweets of roughly 200 Social Bakers users. To build this database, we first make a request to get the most recent 3200 tweets for each user, and then for each of these tweets, we get the most recent 100 retweets.

These adjusted standard errors should account for observed cross- sectional correlation of returns between firms in our sample (Greenwood, 2005; Becker et al., 2013).

B.2 Matching Estimator

The construction of our synthetic matching estimator follows the procedure in Acemoglu et al. (2016). The main idea of this method is to construct a synthetic match for each NDP-, military-, and Islamic-connected firm by using non-connected firms in such a way that the synthetic firm has similar behavior to the actual firm before the event of interest. We construct a synthetic match for each NDP-connected firm by solving the following optimization problem:

$$\forall i \in \mathbb{N}, \{w_j^{i*}\}_{j \in \mathbb{U}} = argmin_{\{w_j^i\}} \sum_i \sum_t \left[R_{it} - \sum_j w_j^i R_{jt} \right]^2$$

subject to

$$\sum_j w_j^i = 1 \text{ and } \forall j \in \mathbb{U}, \forall i \in \mathbb{N}, w_j^i \geq 0,$$

where R_{it} is the return on firm i on pre-event date t, w_j^i is the weight of non-connected firm $j \in \mathbb{U}$ employed in the optimal weighting for NDP-connected firm $i \in \mathbb{N}$. As before, we use all trading days between January 1 and December 23, 2010 as the pre-event window for this estimation.

The return for each synthetic firm is then constructed as

$$\widehat{R_{it}} = \sum_j w_j^{i*} R_{jt}$$

and the abnormal return is computed as the difference between the actual return and the synthetic firm return. To estimate the effect of the event we compute

$$\hat{\phi} = \frac{\sum_i \frac{\sum_{t=n}^{n+m} R_{it} - \widehat{R_{it}}}{\widehat{\sigma_i}}}{\sum_i \widehat{\sigma_i}^{-1}},$$

where $\widehat{\sigma_i}^{-1}$ is a measure of goodness of the match in the pre-event window

$$\widehat{\sigma_i} = \sqrt{\frac{\sum_{t \in \text{pre-event Window}} \left[R_{it} - \widehat{R_{it}} \right]^2}{T}}$$

and T is the number of trading days in the pre-event window. This formula for the average effect of intervention on the treatment group is thus a weighted average formula, with greater weight given to better matches.

To construct the confidence intervals, we randomly draw 500 placebo NDP-connected groups from the non-connected firms, with each group having the same size as the real treatment group, and construct the confidence interval for hypothesis testing of whether the coefficient is significantly different from 0. The effect of the NDP-connection is significant at 5% if it does not belong to the interval that contains the [2.5, 97.5] percentiles of the effect of the NDP-connection for placebo treatment groups.

The matching estimators for military- and Islamic-connected firms are constructed analogously.

Appendix Table 1: Firm Connections by Sector

	NDP	Military	Islamic	Non-connected	All
Agriculture	0	0	0	8	8
Construction	3	0	0	7	10
Consumer Goods	0	1	0	3	4
Education	0	0	0	2	2
Financial Services	4	0	5	23	31
Food and Beverages	2	8	1	10	20
Health Care	1	4	0	6	11
Industrial Manufacturing	3	10	1	23	37
Leisure and Tourism	1	1	0	7	9
Media	0	1	0	0	1
Mining and Metals	2	2	0	3	7
Oil and Gas	0	2	0	2	4
Real Estate	4	0	4	18	23
Services	0	0	0	1	1
Telecommunications	1	0	2	0	3
Transport	1	4	0	1	6
Total	22	33	13	114	177

Notes: The table shows the number of NDP-connected, military-connected, Islamic, non-connected, and all firms in each of the 16 sectors of the economy. There is no overlap between NDP-, military-, and nonconnected firms. Among the 13 Islamic firms, 5 are connected to NDP and the other 8 are connected to neither the NDP nor the military. Definitions of sectors are taken from Zawya.

Appendix Table 2: Mubarak's Fall

	(1)	(2)	(3)	(4)	(5)
Panel A - Alternative Event Windows					
	CR[0,4]	*CR[0,5]*	*CR[0,6]*	*CR[0,7]*	*CR[0,8]*
NDP	-0.058**	-0.097**	-0.104**	-0.124**	-0.131**
	(0.025)	(0.032)	(0.038)	(0.046)	(0.049)
Military	-0.010	0.014	0.005	0.020	0.032
	(0.028)	(0.029)	(0.030)	(0.030)	(0.030)
Islamic	-0.023	-0.033	-0.042	-0.062	-0.064
	(0.040)	(0.039)	(0.042)	(0.047)	(0.051)
R^2	0.231	0.255	0.258	0.285	0.320
N	137	147	147	147	143
Sector F.E.	yes	yes	yes	yes	yes
Standard Controls	yes	yes	yes	yes	yes
Panel B - Winsorized top and bottom firms					
	CR[0,8]				
NDP	-0.129**				
	(0.048)				
Military	0.050*				
	(0.028)				
Islamic	-0.030				
	(0.046)				
R^2	0.281				
N	136				
Sector F.E.	yes				

Notes: Panel A presents variations of the baseline specification in column 2 of Table 2 using different end-dates, m. The table reports only the coefficients of interest and omits covariates in order to save space. See the caption of Table 2 for details. Panel B presents the standard specifications in Table 2 but firms with top or bottom 5% returns are winsorized.

Appendix Table 3: Placebo Events in the Year Prior to Egypt's Arab Spring

	(1)	(2)	(3)
	Nag Hammadi Massacre	Labor Dispute, Strikes	State of Emergency Extended
Panel A	*CR[-270,-269]*	*CR[-192,-190]*	*CR[-185,-184]*
NDP	-0.005	0.021	-0.013
	(0.010)	(0.018)	(0.014)
Military	0.016	0.038	-0.006
	(0.012)	(0.026)	(0.019)
Islamic	-0.004	-0.016	-0.007
	(0.011)	(0.016)	(0.013)
R^2	0.203	0.063	0.060
N	135	136	136
	Satellite Channels Shut Down	Unrest begins in Tunisia	Bin Ali flees Tunisia
Panel B	*CR[-80,-79]*	*CR[-28,-25]*	*CR[-7,-7]*
NDP	-0.003	-0.004	0.002
	(0.009)	(0.006)	(0.005)
Military	0.006	0.011	-0.007
	(0.008)	(0.012)	(0.006)
Islamic	0.010	-0.002	-0.006
	(0.010)	(0.007)	(0.006)
R^2	0.002	0.040	0.084
N	144	147	150

Notes: The table applies our baseline specification from column 2 of Table 2 to different political events in the year prior to Jan 25, 2011. The table reports only the coefficients of interest and omits covariates in order to save space. See the caption of Table 2 for details on the specification. Events in Panel A: 10 dead after attacks on Coptic Christians in the town of Nag Hammadi (worst sectarian violence since 2000); strikes for a higher minimum wage; parliament votes to extend the state of emergency for 2 years; Events in Panel B: government shuts down four independent satellite channels; unrest begins in Tunisia with the self-immolation of street vendor Mohammed Bouazizi; Tunisian president Ben Ali flees the country.

Appendix Table 4: Events during Military Rule

	(1)	(2)	(3)	(4)	(5)	(6)
	Military Crackdown					
	CR[91,117]					*CAR[91,117]*
NDP	0.030	0.004	0.005	0.004	0.010	-0.005
	(0.025)	(0.029)	(0.022)	(0.034)	(0.030)	(0.030)
Military	0.091**	0.080*	0.079**	0.080**	0.084	0.083*
	(0.041)	(0.044)	(0.033)	(0.012)	(0.055)	(0.044)
Islamic	0.008	-0.009	-0.013	-0.009	-0.033	-0.026
	(0.029)	(0.030)	(0.024)	(0.025)	(0.028)	(0.029)
R^2	0.012	0.025	0.096	0.025	-0.013	0.004
N	144	138	138	138	129	138
	Retake Tahrir					
	CR[163,165]					*CAR[163,165]*
NDP	0.009	-0.010	-0.009	-0.010	-0.012	-0.022
	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.018)
Military	-0.019*	-0.024**	-0.003	-0.024**	-0.020**	-0.008
	(0.010)	(0.008)	(0.008)	(0.004)	(0.009)	(0.013)
Islamic	0.003	0.001	-0.006	0.001	0.003	-0.031
	(0.013)	(0.012)	(0.011)	(0.005)	(0.013)	(0.031)
R^2	0.077	0.250	0.140	0.250	0.274	0.347
N	147	141	141	141	131	141
	Presidential Elections 1st round					
	CR[291,292]					*CAR[291,292]*
NDP	-0.009	-0.015	-0.013	-0.015	-0.014*	-0.022
	(0.009)	(0.010)	(0.011)	(0.011)	(0.008)	(0.014)
Military	0.004	0.002	0.009*	0.002	0.003	0.008
	(0.007)	(0.007)	(0.005)	(0.004)	(0.007)	(0.008)
Islamic	0.011	0.010	0.002	0.010**	0.004	-0.008
	(0.008)	(0.008)	(0.007)	(0.005)	(0.010)	(0.014)
R^2	0.042	0.068	0.032	0.068	0.028	0.237
N	131	126	126	126	114	126
	Presidential Elections 2nd round					
	CR[309,310]					*CAR[309,310]*
NDP	0.012	0.018**	0.021**	0.018	0.016**	0.028**
	(0.008)	(0.008)	(0.009)	(0.012)	(0.007)	(0.013)
Military	0.010	0.015*	-0.000	0.015**	0.012	0.004
	(0.009)	(0.009)	(0.008)	(0.004)	(0.008)	(0.012)
Islamic	0.018	0.022*	0.020*	0.022**	0.020**	0.045**
	(0.011)	(0.012)	(0.012)	(0.006)	(0.009)	(0.022)
R^2	0.179	0.241	0.113	0.241	0.272	0.291
N	143	137	137	137	135	137
Sector F.E.	yes	yes	no	yes	yes	yes
β^{World}, β^{Egypt}, β^{unrest}	no	yes	yes	yes	yes	yes
Size, Leverage	no	yes	yes	yes	yes	yes
Weights	no	no	no	no	yes	no
Adjusted S.E.	no	no	no	yes	no	no

Notes: The table reports specifications analogous to those in columns 1-5 and 7 in Table 2 for all events shown in Panel A of Table 3. The table reports only the coefficients of interest and omits covariates in order to save space. See the caption of Table 2 for details.

Appendix Table 5: Events during Military Rule - Matching Estimators

	(1)	(2)	(3)	(4)
	Military Crackdown	Retake Tahrir	Presidential Elections 1st round	2nd round
	CR[91,117]	*CR[163,165]*	*CR[291,292]*	*CR[309,310]*
NDP	0.002	-0.006	-0.019**	0.045***
	[-0.051,0.040]	[-0.022,0.022]	[-0.018,0.020]	[-0.019,0.017]
# Non-connected	97	97	97	97
# NDP-connected	20	20	20	20
Military	0.055***	-0.001	0.006	0.011
	[-0.044,0.028]	[-0.017,0.017]	[-0.015,0.017]	[-0.013,0.019]
# Non-connected	97	97	97	97
# Military-connected	32	32	32	32
Islamic	-0.009	-0.011	-0.014	0.047***
	[-0.061,0.047]	[-0.028,0.026]	[-0.022,0.024]	[-0.022,0.023]
# Non-connected	97	97	97	97
# Islamic-connected	13	13	13	13

Notes: The table reports specifications analogous to those in column 6 in Table 2 for all events shown in Panel A of Table 3. See the caption of Table 2 for details. All columns use the synthetic matching estimator described in detail in Appendix B.2.

Appendix Table 6: Events during Islamist Rule

	(1)	(2)	(3)	(4)	(5)	(6)
	Generals sacked					
	CR[343,344]					*CAR[343,344]*
NDP	-0.001	-0.002	-0.002	-0.002	-0.002	-0.003
	(0.005)	(0.006)	(0.005)	(0.008)	(0.005)	(0.006)
Military	-0.007	-0.004	-0.008	-0.004	-0.002	-0.006
	(0.007)	(0.007)	(0.006)	(0.003)	(0.008)	(0.007)
Islamic	0.009*	0.010*	0.011**	0.010**	0.008	0.015**
	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)	(0.007)
R^2	0.045	0.069	0.070	0.069	0.142	0.206
N	128	122	122	122	117	122
	Consititution passes					
	CR[433,433]					*CAR[433,433]*
NDP	-0.000	-0.011**	-0.012**	-0.011	-0.007	-0.011**
	(0.004)	(0.005)	(0.005)	(0.008)	(0.004)	(0.005)
Military	0.004	0.003	0.001	0.003	0.003	0.002
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
Islamic	0.000	-0.005	-0.004	-0.005	-0.003	-0.002
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
R^2	-0.027	0.050	0.059	0.050	0.132	0.038
N	133	128	128	128	123	128
	Mursi sacked					
	CR[541,562]					*CAR[541,562]*
NDP	0.020	-0.019	-0.010	-0.019	-0.017	-0.016
	(0.020)	(0.021)	(0.019)	(0.032)	(0.019)	(0.022)
Military	-0.005	-0.009	-0.002	-0.009	-0.003	-0.014
	(0.028)	(0.029)	(0.017)	(0.011)	(0.029)	(0.029)
Islamic	-0.026	-0.054**	-0.059**	-0.054**	-0.054**	-0.033**
	(0.019)	(0.016)	(0.017)	(0.020)	(0.016)	(0.014)
R^2	-0.049	0.054	0.097	0.054	0.025	-0.001
N	132	127	127	127	126	127
Sector F.E.	yes	yes	no	yes	yes	yes
β^{World}, β^{Egypt}, β^{unrest}	no	yes	yes	yes	yes	yes
Size, Leverage	no	yes	yes	yes	yes	yes
Weights	no	no	no	no	yes	no
Adjusted S.E.	no	no	no	yes	no	no

Notes: The table reports specifications analogous to those in columns 1-5 and 7 in Table 2 for all events shown in Panel B of Table 3. The table reports only the coefficients of interest and omits covariates in order to save space. See the caption of Table 2 for details.

Appendix Table 7: Events during Islamist Rule - Matching Estimators

	(1)	(2)	(3)
	Generals sacked	Constitution passes	Mursi sacked
	CR[343,344]	*CR[433,433]*	*CR[541,562]*
NDP	0.008**	-0.008**	-0.002
	[-0.009,0.007]	[-0.008,0.009]	[-0.054,0.054]
# Non-connected	97	97	97
# NDP-connected	20	20	20
Military	0.002	0.001	0.007
	[-0.007,0.007]	[-0.008,0.008]	[-0.052,0.043]
# Non-connected	97	97	97
# Military-connected	32	32	32
Islamic	0.015***	-0.003	-0.018
	[-0.012,0.009]	[-0.011,0.014]	[-0.059,0.054]
# Non-connected	97	97	97
# Islamic-connected	13	13	13

Notes: The table reports specifications analogous to those in column 6 in Table 2 for all events shown in Panel B of Table 3. See the caption of Table 2 for details. All columns use the synthetic matching estimator described in detail in Appendix B.2.

Appendix Table 8: Mean Net Purchases of Stock by Insiders as a Percentage of Total Stock Outstanding

	(1)	(2)	(3)	(4)
	Mubarak's Fall	Military Rule	Islamist Rule	Post-Islamist
	-04/17/11	-08/12/12	07/04/13	07/29/13
NDP-connected	-0.02	-0.04	-0.00	-0.01
Military-connected	0.00	-0.47	-0.16	0.00
Islamic-connected	-0.00	-0.11	-0.00	-0.01
Non-connected	0.08	-2.89	-0.60	-0.08

Notes: The table shows the mean across firms of net purchases of stock by insiders of the firm as a share of total stock outstanding in percent for NDP-, military-. Islamic-, and Non-connected firms. For each of the four groups the table also reports the minimum and maximum net purchases across firms.

Appendix Table 9: Portfolio-based estimation

	(1) Events (Table 4)	(2) Protesters (Table 7)
Differences between coefficients		
Incumbent - Other Connected	-0.290***	-1.000***
$p-val$(Incumbent = Unconnected)	0.003	0.000
Connected - Other Connected	0.060	-0.541*
$p-val$(Connected = Unconnected)	0.403	0.007
$p-val$(Equal w/Opp. Sign)	0.165	0.003
$p-val$(Equal w/Opp. Sign), Weighted	0.203	0.003

Notes: The table shows alternative, portfolio-based estimates for the results in Table 4 (column 1) and Table 7 (column 2). The procedure is as follows. We form equal-weighted portfolios of incumbent, other connected, and non-connected firms and run three (seemingly unrelated) time-series regressions of each portfolio return on our event variable (E_t, see caption of Table 4 for details) in column 1 and the number of protesters in Tahrir square (P_t, see caption of Table 7 for details) in column 2. All regressions also control for the world market return on any given day (see section 2 of the main text for details). The table shows hypothesis tests on the coefficients from the seemingly unrelated regressions, where Incumbent - Other Connected refers to the difference of the coefficients on the Event (Tahrir Protesters) variable from the two regressions with the incumbent and the other connected portfolio return as dependent variables, respectively.

Appendix Table 10: Effect of Protests on Stock Market Valuation by Phase

	(1)	(2)	(3)	(4)
	Mubarak's Fall	Military Rule	Islamist Rule	Post-Islamist
	Daily Log Returns × 100			
Incumbent x Tahrir Protesters	-1.193**	-0.912***	0.706	-1.370*
	(0.560)	(0.328)	(0.573)	(0.799)
Connected x Tahrir Protesters	-0.195	0.082	-0.413	-0.199
	(0.589)	(0.360)	(0.342)	(0.540)
R^2	0.610	0.331	0.421	0.424
N	5603	43997	27210	1895
Incumbent	NDP	Military	Islamic	Islamic

Notes: This table shows results from our baseline specification in column 2 of Table 7, estimated separately for each of the four phases of Egypt's Arab Spring. See the caption of Table 7 for details on the specification and Panel B of Table 1 for the beginning and end date of each phase.

Appendix Table 11: Robustness of Results in Table 7

	(1)	(2)	(3)	(4)	(5)	(6)
	Daily Log Returns × *100*					
Incumbent x Tahrir Protesters	-0.749***	-0.727***	-0.751***	-0.751***	-0.766***	-0.751**
	(0.257)	(0.255)	(0.254)	(0.255)	(0.259)	(0.306)
Other Connected x Tahrir Protesters	-0.089	-0.160	-0.161	-0.160	-0.277	-0.160
	(0.228)	(0.217)	(0.217)	(0.218)	(0.226)	(0.242)
R^2	0.409	0.405	0.404		0.458	0.404
N	78705	76359	78705	78705	73297	78705
Include time effect $\times X_i$	yes	yes	yes	yes	yes	no
Include time effect × Fama-French 4 factors	yes	no	no	no	no	no
Include $I\times$ Stock's Daily Trading Volume	no	yes	no	yes	no	no
Include $I\times$ Weekday	no	no	yes	no	yes	no
Newey-West S.E. (5 Lags)	no	no	no	yes	no	no
Drop Firm-Trading Days w/ Firm-Specific News	no	no	no	no	yes	no
Clustered S.E. by firm and sector	no	no	no	no	no	yes

Notes: Ordinary Least Squares estimates of specification

$$R_{it} = I_{it}\ \gamma + (P_t \times I'_{it})\,\gamma^p + X'_i \nu_t + \delta_t + \eta_s + \epsilon_{it}.$$

Dependent variable in all columns is R_{it}, the log return on firm i at time t multiplied by 100. I_{it} denotes a vector of two dummies reflecting connections to the incumbent government and to the two other non-incumbent power groups during each of the four phases of Egypt's Arab Spring, respectively. P_t denotes the number of protesters in Tahrir Square, capped at and normalized with 500,000. X_i denotes the vector of controls that contains β_i^{World}, β_i^{Egypt}, β_i^{Unrest}, and controls for firm-size and leverage. δ_t and η_s are time and sector fixed effects, respectively. All specifications also control for the interaction between I_{it} and the number of (pro-Islamist) protesters in Rabaa Square. Robust standard errors are in parentheses. Column 1 includes each firm's loading on the three Fama-French factors (Rm-Rf, SMB, HML) and Momentum in the vector X_i. All factors are obtained from the WRDS web-site and firms' loadings are constructed as described in section 2. Column 2 controls for the interaction of I_{it} with the stock's daily volume of trade as a fraction of all shares outstanding. Column 3 controls for the interaction of I_{it} with the day of the week. Column 4 re-estimates the standard specification in column 2 of Table 7 using Newey-West standard errors with 5 lags. Column 5 drops firms on days on which they have firm-specific news (that is, on days on which their ticker-symbol appears in the *Mubasher* equity news stream). Column 6 shows two-way clustered S.E. by firm and sector.

Appendix Table 12: Results from Regressions that Drop the Islamist and Post-Islamist Phases

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Excluding Post-Islamist Rule	*Daily Log Returns* $\times$ *100*								
Incumbent x Tahrir Protesters	-0.906***	-0.704***	-0.867***	-0.891***	-0.707***	-0.613**	-0.401	-0.683***	-0.555*
	(0.253)	(0.264)	(0.291)	(0.295)	(0.266)	(0.262)	(0.259)	(0.245)	(0.283)
Other Connected x Tahrir Prot.	-0.359	-0.155	-0.092	-0.106	-0.161	-0.091	-0.037	-0.268	-0.292
	(0.219)	(0.233)	(0.247)	(0.250)	(0.234)	(0.233)	(0.237)	(0.223)	(0.236)
R^2	0.385	0.403	0.337	0.321	0.403	0.403	0.404	0.386	0.404
N	76810	76810	71003	65333	76810	76810	76810	76810	76810
Panel B: Excluding Islamist & Post-Islamist Rule	*Daily Log Returns* $\times$ *100*								
Include time effect $\times X_i$	no	yes	yes	yes	yes	yes	yes	no	no
Drop changes in g'ment or constitution	no	no	yes	yes	no	no	no	no	no
Drop all events analyzed in section 3	no	no	no	yes	no	no	no	no	no
Include firm fixed effect	no	no	no	no	yes	no	no	no	no
Include time effect $\times X_i^2$	no	no	no	no	no	yes	no	no	no
Include sector effect $\times$ Tahrir Protesters	no	no	no	no	no	no	yes	yes	no
Include time effect $\times$ firm effect	no	no	no	no	no	no	no	no	yes

Notes: This table shows specifications identical to those in Table 7 estimated on a restricted sample that drops the post-Islamist phase (Panels A and B) as well as the Islamsit phase (Panel B) of Egypt's Arab Spring. See the caption of Table 7 for details.

Appendix Table 13: Functional Forms

	(1)	(2)	(3)	(4)
	Daily Log Returns × 100			
Incumbent x Tahrir Protesters	-0.751***			
	(0.254)			
Connected x Tahrir Protesters	-0.160			
	(0.216)			
Incumbent x Tahrir Prot. (standardized)		-0.065***		
		(0.022)		
Connected x Tahrir Prot. (standardized)		-0.008		
		(0.025)		
Incumbent x Log(Tahrir Prot. (standardized))			-0.469***	
			(0.174)	
Connected x Log(Tahrir Prot. (standardized))			-0.063	
			(0.165)	
Incumbent x $1_{Tahrir\ Protesters>100k}$				-0.547***
				(0.193)
Connected x $1_{Tahrir\ Protesters>100k}$				-0.110
				(0.150)
R^2	0.404	0.404	0.404	0.404
N	78705	78705	78705	78705

Notes: This table shows variations of the functional form relating returns to the interaction between I_{it} and the number of protesters in Tahrir square. Column 1 reproduces our baseline specification from column 2 in Table 7, where the number of protesters is divided by and capped at 500,000. In column 2, the number of protesters is not capped and standardized by deducting the sample mean and dividing by the sample standard deviation of the number of protesters (the same functional form as in Table 10). Column 3 interacts I_{it} with the log of one plus this standardized number. Column 4 instead uses the interaction between I_{it} and a dummy that is one on days with 100,000 or more protesters in Tahrir square.

Appendix Table 14: Holding Companies Controlled by the Egyptian Military

Holdings Fully Owned by Military	Link to Military	Source
Arab Organization for Industralization (AOI)	It is one of the three main economic military enterprises	http://carnegieendowment.org/2014/06/24/ military-crowds-out-civilian-business-in-egypt ; http://fas.org/nuke/guide/egypt/facility/mark0033.htm
National Service Product Organization (NSPO)	It is one of the three main economic military enterprises	http://carnegieendowment.org/2014/06/24/ military-crowds-out-civilian-business-in-egypt ; http://fas.org/nuke/guide/egypt/facility/mark0033.htm ; http://www.nspo.com.eg/
National Organization for Military Production (NOMP)	It is one of the three main economic military enterprises	http://carnegieendowment.org/2014/06/24/ military-crowds-out-civilian-business-in-egypt; http://fas.org/nuke/guide/egypt/facility/mark0033.htm
Other Evidence of Military Control		
Holding Company for Maritime and Land transport	At least partially owned by the military; Its chairman is an Admiral; the chairman, managing director and board members of affiliated firms are generals (Direct Transport company and Canal Shipping Agencies)	http://www.hcmlt.com/e_mysite/e_board.htm; http://www.merip.org/mer/mer262/ egypts-generals-transnational-capital; http://www.jadaliyya.com/pages/index/4311/ egypts-other-revolution_modernizing-the-military-i
Chemical Industries Holding Company	Affiliated firms are run by generals (National Cement); Major shareholders supervised by members of the military	http://www.zawya.com/middle-east /company/profile/575361/Chemical _Industries_Holding_Company/; http://www.cihc-eg.com/
Egyptian Petrochemicals Company	Major shareholder of affiliated firms is the main business partner of the military; Affiliated firms have generals on the board	https://www.zawya.com/middle-east/company /profile/361753/Egyptian_Petrochemicals_Company/; https://www.zawya.com/company/profile /1000990/Egyptian_Petrochemicals_Holding_Company/ ; www.merip.org/mer/mer262/egypts-generals-transnational-capital
Egyptian Natural Gas Holding Company	Joint venture with one of the military enterprises (NOMP), they both own Tharwa Petroleum; Major shareholder is prominent business partner of the military	http://www.tharwa.com.eg/wps/portal/tharwa _inner?WCM_GLOBAL_CONTEXT=/wps/wcm/connect /tharwa/Tharwa/Investors/Investors; www.merip.org/mer/mer262/egypts-generals-transnational-capital; https://www.zawya.com/middle-east/company/profile/4898 /Egypt_Kuwait_Holding_Company_via_National_Energy_Company/
Holding Company for Metallurgical Industries	Its subsidiary is managed by a general (National Cement)	http://www.zawya.com/company/profile /306066/Metallurgical_Industries_Company/ http://www.zawya.com/middle-east/company /profile/4897/Egyptian_Iron__Steel_Company/;
Holding Company for food industries	The chairman and managing directors and board members of affiliated firms are generals (General Silos and Storage). Affiliated firm (Egyptian Sugar and Integrated Industries Company) has a general representing its ownership stake in Delta Sugar	https://www.zawya.com/middle-east/company/profile /4947/Holding_Company_for_Food_Industries/ ; https://www.zawya.com/middle-east/company/profile /1001684/Egyptian_Sugar _and_Integrated_Industries_Company/
Holding Company for spinning and weaving	The products of its affiliated firms (KABO) are described as part of the military economic empire	http://www.egypt-business.com/Paper/details/1206-xg-The- Egyptian-Military-between-Politics-and-Economy/3808); http://deficientbrain.blogspot.co.uk/2013 /08/al-sisis-underwear-manufacturer-hacked.html
Holding Company for Pharmaceuticals	It holds its shareholder meetings regularly in a military installation (The Engineering Authority of the Armed Forces)	http://alexcopharma.net/En/Assembly.aspx; http://www.holdipharma.com /en/home/Pages/alexandria.aspx
Holding Company for Tourism, Hotels & Cinema	Its main subsidiary (The Egyptian General Company for Tourism and Hotels) hires a general as the chairman and managing director of one of its main affiliated firms	https://www.zawya.com/middle-east/company/profile /438653/Holding_Company_for_Tourism_Hotels__Cinema/; https://www.zawya.com/company/profile/421198/The _Egyptian_General_Company_for_Tourism_and_Hotels/

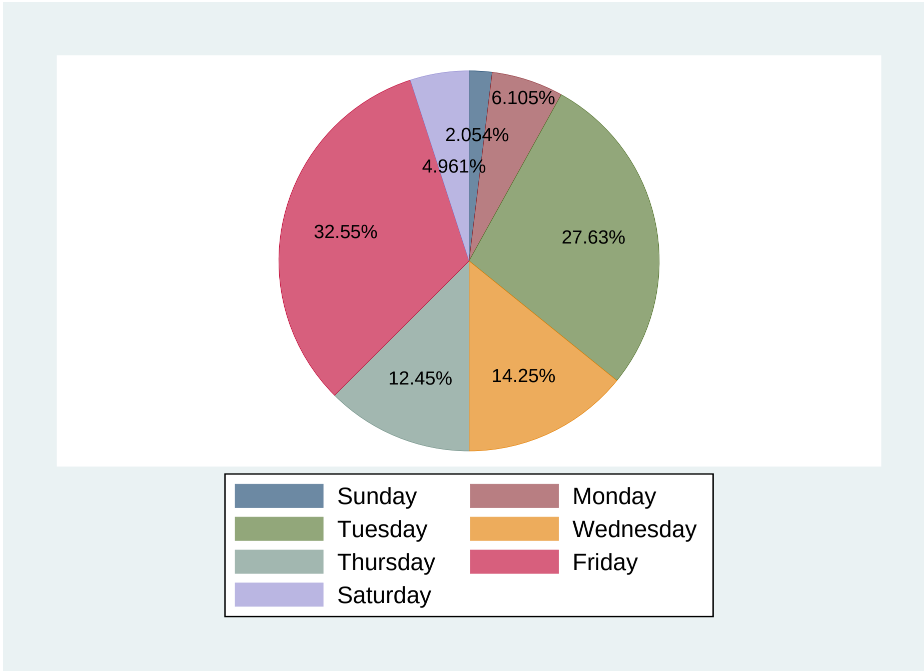
Appendix Table 15: Sample of Mapping from Words in Newspaper Articles to Numbers

Word	*Number*
a thousand	1,000
few thousand	2,000
several thousand	3,000
less than several thousand	2,500
less than a thousand	750
under a thousand	750
more than a thousand	1,250
over a thousand	1,250
thousands	5,000
tens of thousands	50,000
hundreds of thousands	500,000
over a quarter-million	300,000

Appendix Table 16: List of Twitter Accounts of Prominent Opposition Figures

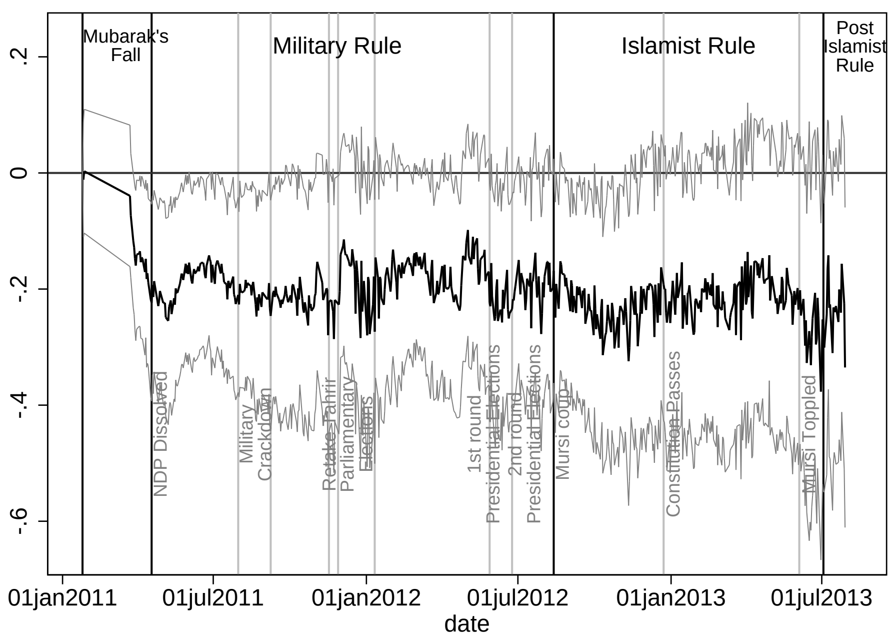
Phase of Egypt's Arab Spring	Twitter Users Included in Opposition Count
Mubarak's Fall	ElBaradei HamdeenSabahy HamzawyAmr shabab6april GhostyMaher moussacampaign M6april Khaledali251 GalalAmer Dr_Heba_Raouf DrEssamSharaf DrAbolfotoh AsmaaMahfouz DrBassemYoussef amrkhaled belalfadl YosriFouda amrwaked Ghonim AlaaAswany NaguibSawiris AymanNour GameelaIsmail Youssefalhosiny amremoussa HamdyKandil alnagar80 nawaranegm bothainakamel1 Ibrahim_essa3 Reemmagued Elshaheeed Dinabdelrahman SalmaSabahy MohamedAbuHamed ElBaradeiOffice MohammadSawy Ibrahim_3eissa FatimaNaoot waelabbas moiegy MahmoudSaadpage ONtvLIVE SamiraIbrahim4 SabahyCampaign MasreyeenAhrrar Madaneya2012 waelabdelfattah SalafyoCosta Hezb_Elnoor naderbakkar Alwasatpartyeg arahmanyusuf MoatazAFattah MuhammadMorsi Essam_Sultan Essam_Elerian MustafaHosny alqaradawy Saad_Elkatatny FJparty HazemSalahTW ajmmisr almorshid khairatAlshater FadelSoliman El_Awa MohmedAlbeltagy m_abotrekh ikhwantawasol ANAS_ELSHAER NabdAlekhwan khairatelshater
Military Rule	ElBaradei HamdeenSabahy HamzawyAmr shabab6april GhostyMaher moussacampaign M6april Khaledali251 GalalAmer Dr_Heba_Raouf DrEssamSharaf DrAbolfotoh AsmaaMahfouz DrBassemYoussef amrkhaled belalfadl YosriFouda amrwaked Ghonim AlaaAswany NaguibSawiris AymanNour GameelaIsmail Youssefalhosiny amremoussa HamdyKandil alnagar80 nawaranegm bothainakamel1 Ibrahim_essa3 Reemmagued Elshaheeed Dinabdelrahman SalmaSabahy MohamedAbuHamed ElBaradeiOffice MohammadSawy Ibrahim_3eissa FatimaNaoot waelabbas moiegy MahmoudSaadpage ONtvLIVE SamiraIbrahim4 SabahyCampaign MasreyeenAhrrar Madaneya2012 waelabdelfattah SalafyoCosta arahmanyusuf MoatazAFattah
Islamist Rule	ElBaradei HamdeenSabahy HamzawyAmr shabab6april GhostyMaher Khairy_Ramadan moussacampaign M6april Khaledali251 GalalAmer Dr_Heba_Raouf DrEssamSharaf AsmaaMahfouz DrBassemYoussef belalfadl YosriFouda amrwaked Ghonim AlaaAswany NaguibSawiris AymanNour GameelaIsmail Youssefalhosiny amremoussa HamdyKandil alnagar80 nawaranegm bothainakamel1 Ibrahim_essa3 Reemmagued Elshaheeed Dinabdelrahman SalmaSabahy MohamedAbuHamed ElBaradeiOffice MohammadSawy Ibrahim_3eissa FatimaNaoot waelabbas moiegy MahmoudSaadpage ONtvLIVE SamiraIbrahim4 SabahyCampaign tamarrod MasreyeenAhrrar Madaneya2012 waelabdelfattah SalafyoCosta arahmanyusuf MoatazAFattah lameesh BakryMP EgyArmySpox Lamees_Alhadidi AhmedShafikEG
Post-Islamist Rule	ElBaradei HamdeenSabahy HamzawyAmr Khairy_Ramadan moussacampaign Khaledali251 GalalAmer Dr_Heba_Raouf DrEssamSharaf AsmaaMahfouz DrBassemYoussef belalfadl YosriFouda amrwaked Ghonim AlaaAswany NaguibSawiris AymanNour GameelaIsmail Youssefalhosiny amremoussa HamdyKandil alnagar80 nawaranegm bothainakamel1 Ibrahim_essa3 Reemmagued Elshaheeed Dinabdelrahman SalmaSabahy MohamedAbuHamed ElBaradeiOffice MohammadSawy Ibrahim_3eissa FatimaNaoot waelabbas moiegy MahmoudSaadpage ONtvLIVE SamiraIbrahim4 SabahyCampaign tamarrod MasreyeenAhrrar Madaneya2012 waelabdelfattah SalafyoCosta arahmanyusuf MoatazAFattah lameesh BakryMP EgyArmySpox Lamees_Alhadidi AhmedShafikEG Hezb_Elnoor naderbakkar

Appendix Figure 1: Number of Protesters by Weekday



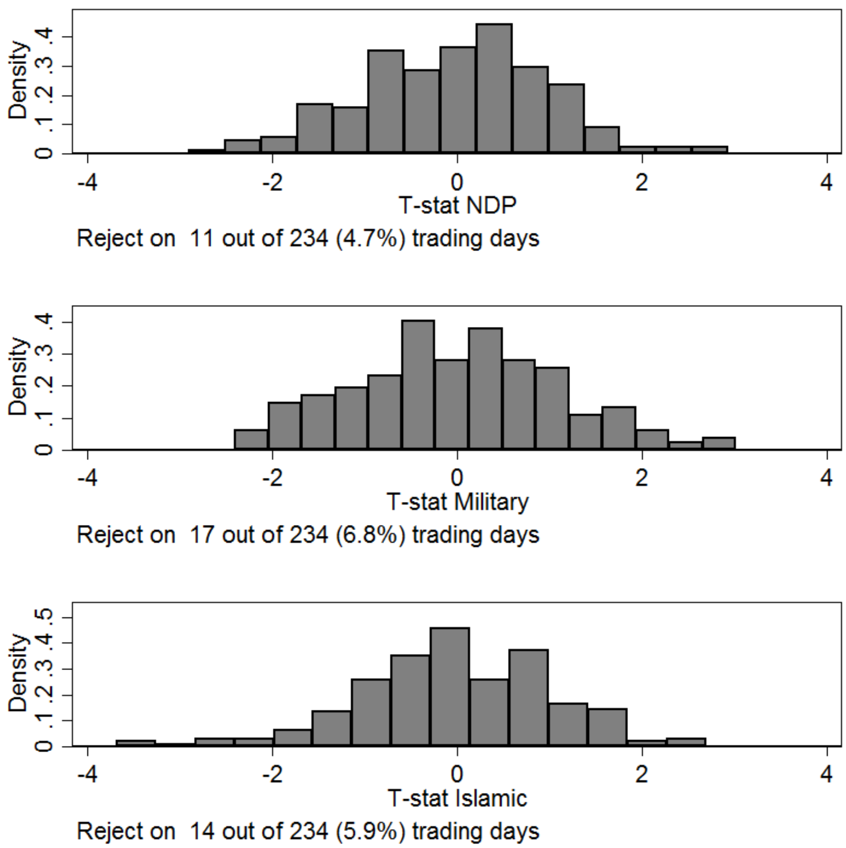
Note: The figure shows the percentage of all protesters that turned out in Tahrir Square between January 25, 2011, and July 30, 2013, by weekday. See Section 2 of the main text for details.

Appendix Figure 2: Persistence of the Effect of Mubarak's Fall on NDP-connected Firms



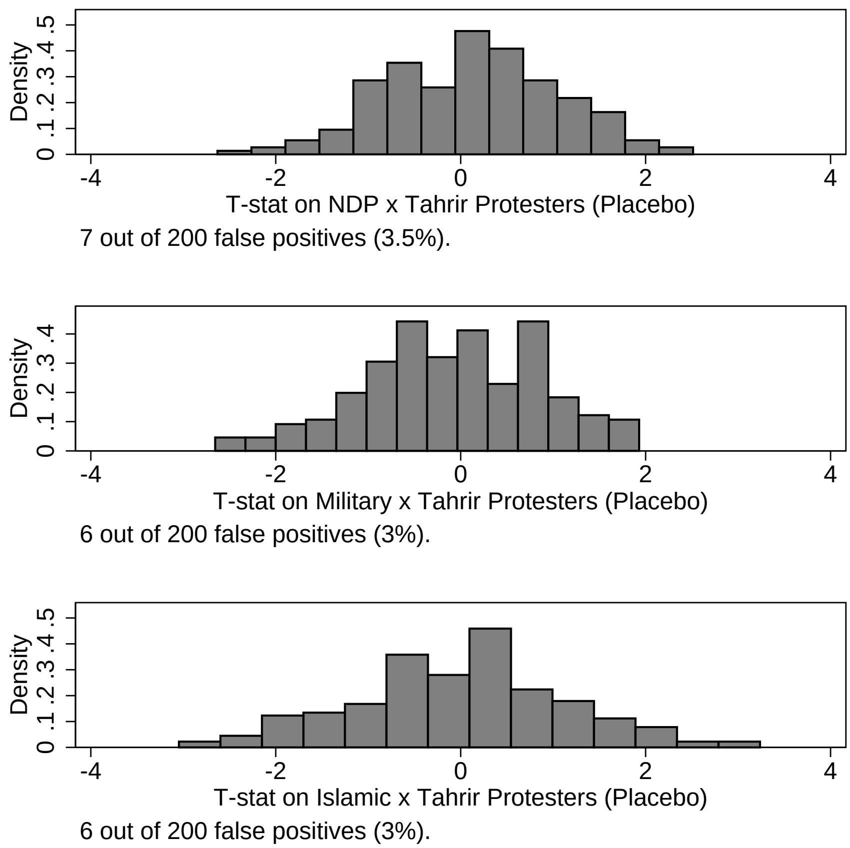
Note: Coefficients and 95% confidence intervals on the dummy variable for NDP-connected firms in specifications corresponding to column 2 of Table 2. The figure shows coefficients for cumulatively longer event windows beginning on January 25, 2011 (event trading day 0), and ending on the date indicated.

Appendix Figure 3: Placebo Regressions for all Trading Days in 2010



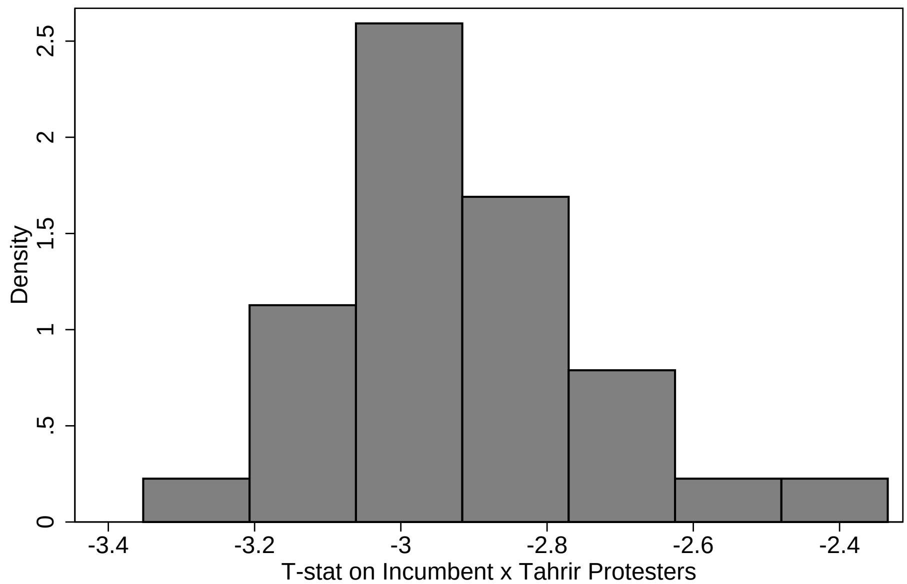
Note: Histograms on T-statistics on the dummy variables for connected firms in specifications corresponding to column 2 of Table 2. The figure shows histograms of T-statistics obtained from running the baseline specification in column 2 of Table 2 for each trading day between January 1, 2010, and November 30, 2010.

Appendix Figure 4: Histograms of T-Statistics from Placebo Regressions for Specification (2)



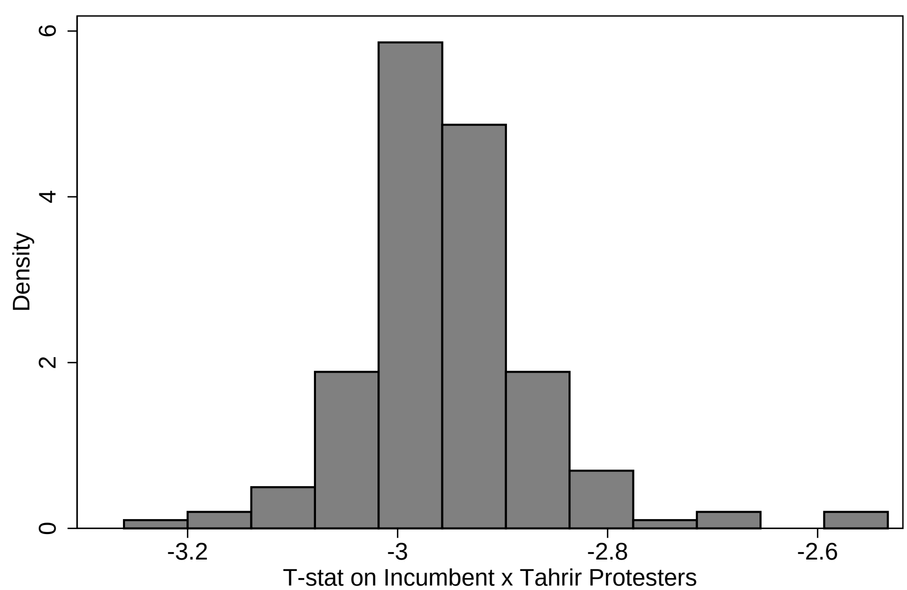
Note: The figure shows the results of a placebo experiment in which we use the sample distribution of the number of protesters in Tahrir square between Jan 1, 2011 and July 30, 2013 to randomly assign a number of protesters to trading days between January 1 and November 30, 2010. We then estimate specification (2) using the fictitious data. The figure shows results obtained from 200 random assignments of protesters to trading days, where the three panels show histograms of the t-statistics on the interaction of dummies for NDP-, military-, and Islamic-connected firms with the fictitious number of protesters, respectively.

Appendix Figure 5: Distribution of T-statistics when Falsely Classifying one of the 61 Connected firms as Non-connected



Note: The histogram shows T-statistics on the interaction of the dummy variable for incumbent firms with the number of protesters in Tahrir square from a robustness exercise where we falsely classify one of the 61 connected firms as non-connected and re-estimate the specification in column 2 of Table 7.

Appendix Figure 6: Distribution of T-statistics when Dropping Individual Firms



Note: The histogram shows T-statistics on the interaction of the dummy variable for incumbent firms with the number of protesters in Tahrir square from a robustness exercise where we drop one of the 177 firms from the data set and re-estimate the specification in column 2 of Table 7.