Political Uncertainty and Commodity Prices

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Abstract

We examine the effect of political uncertainty on commodity prices. Using a comprehensive sample of 87 major commodities traded in 12 countries over the 1960-2017 period, we show that political uncertainty, proxied by U.S. presidential elections, has a significant impact on commodity prices worldwide. On average, commodity prices decline by 6.4% in the quarter leading up to the U.S. presidential elections. This effect is stronger for close elections and during recession periods. Interestingly, non-U.S. local elections have an insignificant impact on those countries' commodity prices. These findings suggest that commodities cannot be used as a hedge against political risk.

1. Introduction

Over the past decade there have been two major developments in the commodity markets. First, under a common perception of diversification benefits, commodities have become an attractive asset class for portfolio managers (Tang and Xiong, 2012; Cheng and Xiong, 2014). Consequently, the trading volume of commodity contracts experiences a 460% increase from 0.8 billion contracts in 2005 to 4.6 billion contracts in 2015 (Acworth, 2016). Second, the volatility of commodity prices has increased substantially relative to the prices of other assets such as equities and bonds. These two phenomena give rise to a fundamental question on what drives commodity prices and, more specifically, how does economy-wide uncertainties affect the variation of commodity prices. In this paper, we focus on a particular form of uncertainty, political uncertainty, and examine its impact on commodity prices.

Political uncertainty has been prominently featured in recent academic research and policy discussions (e.g., Durnev, 2010; Boutchkova et al., 2012; Julio and Yook, 2012; Baker, Bloom, and Davis, 2016).[1] In particular, several studies shows that political uncertainty negatively affects the value of financial assets such as bonds (Gao and Qi, 2013; Huang et al., 2015) and equities (Brogaard and Detzel, 2015; Brogaardet al., 2017). Situated between the real economy and financial markets, commodities should also be affected by political uncertainty. However, the direction of the effect is not as obvious as those on bond and equities.

On the *demand* side, political uncertainty could either decrease or increase the demand for commodities. As demonstrated by Julio and Yook (2012) and Jens (2016), political uncertainty causes firms to reduce investment expenditures until the uncertainty is resolved. Because commodities are raw inputs for the production process, if firms delay production during periods of high political uncertainty, their demand for commodities would shrink. Furthermore, Baker, Bloom and Davis (2016) show that household consumption drops during

[1] In its Global Economic Prospects (2016), World Bank writes, "The heightened level of policy uncertainty, especially regarding trade, has been exacerbated by recent political developments–most notably in the United States and the United Kingdom… may be amplified over time by mounting protectionist tendencies, slower potential growth and elevated vulnerabilities in some emerging markets and developing countries."

periods of high political uncertainty, which could also contribute to lower demand for commodities. On the other hand, in fear of commodity shortages during politically unstable periods, firms and households may choose to accumulate inventories in advance (Hong, Paula, and Singh, 2016). Similarly, speculators are likely to hoard in physical and futures markets during uncertain times (Tang and Xiong, 2012; Kilian and Murphy, 2014).

On the *supply* side, due to irreversibility of investment and large shutdown costs, commodity supply is much more inelastic than commodity demand. That is, commodity producers may not be flexible enough to adjust their production in dealing with political uncertainty. Therefore, commodity supply may not change by much during periods of high political uncertainty. However, when faced persistent political unrest and turmoil, commodity producers may be forced to cut back on their production and lay off workers. For example, the prolonged political tension in Venezuela has significantly curtailed its oil production in recent years.

Ultimately, the impact of political uncertainty on commodity prices is determined by the equilibrium between demand and supply, and should be tested empirically. One challenge in cleanly identifying the effect of political uncertainty is that it can be conflated with other factors such as economic uncertainty (Baker and Bloom (2013)). To address this challenge, we follow the recent literature (e.g., Julio and Yook, 2012; Kelly, Pastor and Veronesi, 2016; Broggard et al., 2017) and use elections as an exogenous measure of political uncertainty. We focus primarily on U.S. presidential elections and examine how worldwide commodity prices vary with the U.S. presidential election cycles.

We choose to focus on U.S. presidential elections to assess the price impact of political uncertainty for several reasons. First, U.S. presidential elections affect its economic performance because they may result in changes in the country's fiscal and monetary policies, industry and trade, regulations, and taxation policies (e.g., Julio and Yook, 2012; Baker, Bloom, and Davis 2016; Jens 2016). Second, the U.S. not only has the largest commodity futures market in the world but also is the largest commodity producer and the second-largest commodity consumer. Third, the timing of U.S. presidential elections was instituted by the Congress in 1845, and therefore is independent from local and global economic conditions, allowing us to isolate the effect of political uncertainty from other confounding factors.

We conduct our analysis using a comprehensive sample of 87 major commodities traded in 12 countries over the 1960-2017 sample period. Specifically, we treat the quarter prior to an U.S. presidential election as a period of high political uncertainty and perform difference-in-difference (DD) panel regressions.[2] Several important findings emerge. First, we find that political uncertainty has a significant negative effect on commodity prices worldwide. On average, commodity prices decline by 6.4% (4.6% for commodities traded in the U.S. and 8.5% for commodities traded in other countries) in the quarter leading up to an U.S. presidential election. This is consistent with the hypothesis that demand for commodities decreases during periods of elevated political uncertainty, causing their prices to drop (Julio and Yook, 2012; Jens, 2016; and Baker, Bloom and Davis, 2016). For commodities traded outside the U.S., we also control for the effect of local elections, but, surprisingly, find that local elections have an insignificant effect on commodity prices. In other words, prices of commodities traded outside the U.S. are more sensitive to the uncertainty surrounding U.S. presidential elections than to that of local elections. This result supports the view that commodities are priced globally due to international trades and arbitrages (Casassus, Liu and Tang, 2013). At the same time, it highlights the importance of U.S. presidential elections to the global commodity markets.

Second, we explore whether there exists heterogeneity in the baseline results across countries or commodities. Specifically, we perform the DD analysis for each of 12 countries or five categories of commodities: Energy, Industrial Materials, Precious Metals, Green Seeds, and Softs and Live Cattle. We find that the decline in commodity prices prior to U.S. presidential elections is persistent across both individual countries and commodity categories. Moreover, we show that our baseline finding is robust to a number of alternative specifications such as including additional control variables and calculating commodity spot prices using alternative methods.

Third, we study whether the commodity price impact of political uncertainty is influenced by factors such as commodity market integration, the degree of political

[2] Our treatment is consistent with Jens (2016), who shows that firm investments begin to decline one quarter prior to U.S. presidential elections.

uncertainty, and economic conditions. To examine the role of commodity market integration, we classify commodities into local and global commodities based on their return correlations with the international commodity market index. We find that local commodities, relative to global ones, experience a smaller price decline in the quarter prior to U.S. elections, suggesting that commodities that are segmented from the global commodity markets are less sensitive to global political uncertainty (proxied by U.S. presidential elections). Concerning the degree of political uncertainty, we find that close (and hence more uncertain) U.S. elections are associated with a 10% larger price decline in commodity prices than elections that are not close, suggesting that a higher degree of political uncertainty results in a bigger impact on commodity prices. Finally, Pastor and Veronesi (2013) argue that political uncertainty tends to have a stronger impact on asset prices during recessions because governments are likely to adopt new policies in a weak economy. Consistent with this, we observe a larger commodity price decline prior to U.S. elections taking place during recessions.

In the last test, we check whether commodity prices recover after political uncertainty is resolved. We do not find evidence of a significant price rebound after U.S. presidential elections. This is consistent with the results of Julio and Yook (2012) and Jens (2016) and suggests that even after the election of a new president, there remains significant uncertainty about when and how the new president’s policies will be implemented.

Our study lies at the intersection of two major strands of literature: one on how political uncertainty affects financial markets and the other on what determines commodity prices. The first literature includes papers studying the effects of political uncertainty on asset prices (Pastor and Veronesi, 2012, 2013; Gao and Qi, 2013; Brogaard and Detzel, 2015; Huang et al., 2015; Kelly, Pastor, and Veronesi, 2016; Brogaard et al, 2017) as well as how asset prices vary with presidential election cycles (Santa-Clara and Valkanov, 2003; Belo, Gala, and Li, 2012; Boutchkova et al., 2012). To the best of our knowledge, our study is the first to investigate the effect of political uncertainty on commodity prices. Our empirical findings also advance the understanding of determinants of commodity prices. For example, the theory of storage (e.g., Brennan 1958; Routledge, Seppi, and Spatt 2000; Pindyck 2001; Gorton, Hayashi, and Rouwenhorst 2013) proposes that basis is a key determining factor of commodity prices. In addition, Asness, Moskowitz and Pedersen (2013), Tang and Xiong (2012), Gorton and Rouwenhosrt (2006) and Frankel (2008) show that lagged price movements, equity market returns, and real interest rates are also important in explaining commodity price movements. Using a sample of 87 major commodities from 12 countries, we contribute to this literature by performing a comprehensive study on global commodity prices and identifying political uncertainty as an important source of variation in commodity prices. Contrary to the conventional wisdom, we find little support of commodities as a hedge against political uncertainty.

The rest of the paper proceeds as follows. Section 2 describes the data used in this paper. Section 3 introduces our DD framework, presents the results of the baseline regression, and explores the variation of the baseline results across different subsamples and different economic and political conditions. Section 4 presents a number of additional robustness checks. Section 5 concludes.

2. Data Description

In this section, we describe data on commodity prices, elections, and control variables in our empirical analysis.

2.1 Futures Data

We collect price data on 87 commodities traded on 20 exchanges from 12 countries around the world: the US (30 commodities), France (3), China (11), the U.K. (14), Japan (9), India (7), Brazil (3), South Africa (5), Canada (1), the UAE (1), Singapore (2), and Malaysia (1). These 12 countries are generally either major commodity consumers or exporters. Panel A of Table 1 reports the summary information of the commodities from each country (detailed information on individual commodities is provided in Appendix A). We see that commodity contracts from developed countries normally have much earlier starting dates than those from developing countries. For 80 of the 87 commodities studied, the futures prices are obtained from the Commodity Research Bureau (CRB) dataset. The remaining seven commodities are copper, aluminum, aluminum alloy, lead, nickel, zinc and tin, all of which are traded on the London Metal Exchange (LME). Their spot prices are obtained from

Datastream. Note that the CRB data originally contain more than 200 commodity contracts. We delete mini contracts and contracts traded on electronic platforms and contracts that start later than 2010. We also drop illiquid commodity contracts with an average of more than four non-trading days within a month. The final sample consists of 116,302 commodity/week observations from June 1, 1960 to February 7, 2017.

Since the LME trades spot metals, spot prices are directly available for seven commodities in our dataset. For the remaining 80 commodities whose spot prices are not directly available, we follow Pindyck (2001) and back out the spot prices through a linear interpolation of the log prices of the nearby and second nearby futures contracts:

$$\ln(S_t) = \ln\big(F(t,T_1)\big) + \frac{T_1 - t}{T_2 - T_1}\ln\Big[\frac{F(t,T_1)}{F(t,T_2)}\Big], \tag{1}$$

where S_t is the spot commodity price, $F(t,T)$ is the futures price at time t with maturity T, and T_1 and T_2 are the maturities of the nearby and second nearby futures contracts, respectively. Using spot prices, we calculate spot returns following $R_t = \frac{S_t - S_{t-1}}{S_{t-1}}$. In addition, we calculate the (log) basis, B_t, of individual commodities as follows:

$$B_t = \frac{\ln(F(t,T_2)) - \ln(F(t,T_1))}{T_2 - T_1} = \frac{\ln(F(t,T_1)) - \ln(S_t)}{T_1 - t}. \tag{2}$$

Note that the second equality in equation (2) holds because log spot prices are backed out through a liner interpolation of futures prices.

Panels A Table 1 shows that spot prices on average grow at a rate of 15 basis points per week, approximately 8% per year with an annualized volatility of 30%. The average basis is approximately 2%, slightly in contango with a volatility of 23%. We also group the commodities into five categories: Energy (11 commodities), Industrial Materials (20), Precious Metals (7), Green Seeds (34), and Softs and Live Cattle (15). Panel B of Table 1 reports the summary statistics for each category. The growth rates range from 30 basis points per week for Energy to 13 basis points per week for Industrial Materials, and the volatilities ranges from 6.94% for Energy to 3.83% for Precious Metals. The bases are positive for all categories, ranging from 2.62% for Green Seeds to 1.93% for Precious Metals.

2.2 Control Variables

We collect weekly equity index returns and 3-month Treasury bond interest rates for the

12 countries from Bloomberg and Datastream over the 1960-2017 sample period. Panel C of Table 1 reports the average stock market index return and interest rate for each country.[3] The average annualized equity index return is 14% with a volatility of 24%, and the average interest rate is 4% with a volatility of approximately 2%.

We also download the Chicago Fed National Activity Index (CFNAI) from the Chicago Fed website from January 1968 to February 2017. To convert the monthly index to a weekly frequency, we assign the CFNAI value, announced on the first day of each month, to each of the four weeks within that month. We also obtain the NBER recession dates from the NBER website (http://www.nber.org/cycles.html). In addition, we collect historical public polling data for U.S. presidential elections from the Gallup Organization for 1960-2017. Finally, weekly VIX, U.S. Dollar and Baltic Dry Index (BDI) indices are downloaded from Datastream from May 1990 to February 2017.

2.3 Election Data

We obtain national election data for the 12 countries from the Polity IV Project, conducted by the Center for Systemic Peace and Conflict Management at the University of Maryland, over the 1960-2017 sample period. We further compare our data with data from the World Bank Political Institution database and correct erroneous or missing data with various online sources. The same datasets are used by Julio and Yook (2012) and Huang et al. (2015). We follow Julio and Yook (2012) and classify the national elections in each country as following either a presidential system, a parliamentary system, or others. Table 2 shows that out of the 12 countries in our sample, two countries follow a presidential system and seven follow a parliamentary system. The remaining three countries follow alternative political systems. Specifically, France has a hybrid system combining the features of both the presidential and parliamentary systems. We follow Julio and Yook (2012) to focus on its presidential rather than legislative elections because it is commonly known that the French President holds more executive power than the Prime Minister. China's elections are based on

[3] Note that Brazil experiences hyperinflation during the sample period. Hence, we have an average annualized index return of more than 70%.

a hierarchical electoral system. The President and the State Council of China are elected by the National People's Congress. Governors, mayors, and heads of counties, districts, townships and towns are elected by local People's Congresses.[4] The UAE does not hold national elections but instead follow a system of a federal, presidential, and absolute monarchy. According to convention, the Emir of Abu Dhabi is the President of the UAE and the head of state, and the Emir of Dubai is the Prime Minister and the head of government.[5]

Exogenous timing of elections is an important consideration in studying the impact of political uncertainty on asset prices. As shown in Table 2, the U.S., France, China and Brazil have fixed election calendars (by law or convention), and therefore the timing of elections is exogenous. The U.K., India, Malaysia, South Africa, Japan, Canada and Singapore permit early elections, which raises the question of endogeneity. To address this issue, we perform a robustness check by estimating our baseline regression separately for countries with exogenous vs. endogenous election timings. The average time interval between two elections is 4.0 years with a standard deviation of 1.1 years; the minimum and maximum values are nine months and seven years, respectively.

3. Empirical Results

This section presents the empirical results of studying the impact of political uncertainty as measured by national elections on commodity prices. As the U.S. is the largest economy in the world and a major consumer and producer of commodities, we view the U.S. presidential elections as a major source of political uncertainty globally but also explore the role of national elections in other countries in influencing their commodity prices. We begin with a baseline regression of commodity prices on national elections, after which we investigate the variation in the baseline results across countries, commodity categories, business cycles, and election closeness. Finally, we analyze the commodity price behavior during post-election periods.

[4] See https://en.wikipedia.org/wiki/Elections_in_China.
[5] See https://en.wikipedia.org/wiki/Politics_of_the_United_Arab_Emirates#Legislature.

3.1 The Baseline Regression

Our baseline regression is designed to capture the differences in commodity price behavior between periods of high and low political uncertainty. We define the one or two quarters prior to elections as periods of high political uncertainty and other periods as periods of low political uncertainty. Because commodity prices exhibit seasonality (Sorensen 2002) and are likely to be influenced by election cycles, we run a difference-in-difference (DD) regression:

$$R_{i,j,t} = b_1 DQ_t + b_2 DY_t + b_3 DQ_t \times DY_t + b_4 \Delta B_{i,j,t} + b_5 R^e_{j,t} + b_6 \Delta I_{j,t}$$

$$+ \sum_{k=1}^{52} c_k R_{i,j,t-k} + u_i + \varepsilon_{i,j,t}, \tag{3}$$

where the dependent variable $R_{i,j,t}$ is the arithmetic spot return of commodity *i* from country *j* in week *t*. The explanatory variable DQ_t is equal to one when week *t* falls into the one- or two-quarter period before the election in a given year and zero otherwise, and DY_t is equal to one when week *t* falls into the one-year period leading up to an election and zero otherwise. For countries with flexible election dates, we assume the next election date is identical to the previous one until one year before the next election, and the actual election date is used afterwards.

Equation (3) essentially uses commodity returns during normal times (without upcoming elections) as the control to determine the price effect of political uncertainty surrounding upcoming elections.[6] The coefficient on DQ_t captures the seasonality (time of year) effect of commodities. The coefficient on DY_t captures the effect of election cycles–the return differences between pre-election years and other years. The DD coefficient on the cross term $DQ_t \times DY_t$ thus captures the marginal effect of high political uncertainty (during the quarter or two quarters prior to an election) on commodity prices, the focus of our analysis.

Control variables are defined as follows. $\Delta B_{i,j,t}$ is the change in basis, $R^e_{j,t}$ is the return of the equity market index in country *j*, $\Delta I_{j,t}$ is the interest rate change in country *j*, $R_{i,j,t-k}$ is the commodity return in week *t-k*, and u_i captures the commodity-fixed effect.[7] We use

[6] Similar DD regressions are used in Jens (2016) to study the impact of gubernatorial elections on firm investment behavior.

[7] Pindyck (1993) argues that under a present value model, commodity prices should co-move with basis as the latter is

the double-clustering methodology as shown in Petersen (2009) to obtain the standard errors of coefficients in the panel regression.

Table 3 reports the estimation results for Equation (3) under various specifications. The first six regressions in both Panels A and B show a negative and significant DD coefficient, suggesting that U.S. presidential elections have a large negative impact on worldwide commodity prices. On average, global commodity prices fall by 6.4% ($0.494\% \times 13$) and 8.0% ($0.306\% \times 26$), respectively, over one and two quarters prior to U.S. elections. This decline in commodity prices is experienced by both commodities traded in the U.S. and those traded in other countries. U.S. commodity prices decrease by 4.6% ($0.355\% \times 13$) and 7.3% ($0.279\% \times 26$), respectively, over one and two quarters before presidential elections; the corresponding numbers for non-U.S. commodities are 8.6% ($0.658\% \times 13$) and 8.5% ($0.325\% \times 26$). Overall, the magnitudes of these effects are very large economically.

Julio and Yook (2012) and Jens (2016) show that firms invest less before elections than during normal times due to high political uncertainty. Because commodities are usually inputs of firm production, less investment leads to less demand for commodities. In addition, Baker, Bloom and Davis (2016) document that household consumption drops during periods of high political uncertainty, which would also lower demand for commodities. A lack of demand from both firms and households would thus cause prices to drop, and this can explain the negative returns experienced by commodities before U.S. presidential elections. On the other hand, the evidence is inconsistent with the hypothesis of firms and speculators hoarding during politically uncertain periods, which would lead to a surge in demand and hence prices. It is also inconsistent with the hypothesis that political uncertainty disrupts commodity production, thus causing supply to decrease and prices to rise.

The last two regressions in Panels A and B show that non-U.S. elections have a negative but insignificant impact on non-U.S. commodities, and the magnitude of the effect is

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the future benefit of holding a commodity. Consequently, commodity returns should be explained by changes in basis. Tang and Xiong (2012) document a significant relation between stock returns and commodity returns caused by a spillover effect from the mainstream financial markets to commodity markets. Frankel (2008) shows that commodity prices have a negative relation with the level of interest rates and argue that this is because high interest rates cause a large marginal cost of inventory carry on commodities. On the other hand, Gorton and Rouwenhorst (2006) and Tang and Xiong (2012) document a negative relation between bond returns and commodity returns, which implies a positive relation between interest rates and commodity prices. Asness, Moskowitz, and Pedersen (2013) show a momentum effect in commodity futures for up to one year.

economically very small. Specifically, commodity prices decline by approximately 1.0% ($0.080\% \times 13$) and 0.2% ($0.006\% \times 26$), respectively, over one and two quarters prior to their local national elections.

The fact that U.S. elections seem to have a much larger influence on global commodity prices than non-U.S. elections can come from several sources. First, the U.S. is the world's largest economy with the most political power, and its policies tend to extend beyond its borders and affect other countries. From this perspective, U.S. political uncertainty should be regarded as a *systematic* risk factor worldwide. Second, the U.S. economy has strong linkages to other economies through real trade. U.S. political uncertainty can thus influence the economies of other countries through these real links. For example, less demand by U.S. firms (caused by high political uncertainty) can lead to fewer exports from other countries and, consequently, lower commodity prices in other countries. Third, as Casassus, Liu and Tang (2013) show, many commodities are substitutes, inputs/outputs to each other. When price discrepancies appear in different commodity markets, arbitrageurs can correct these discrepancies through physical trades or financial transactions. For this reason, different commodities and similar commodities from different locations tend to co-move. This results in globally determined demand and supply and global pricing for commodities. Consistent with the above arguments, ABC news reporter McCosker (2016) writes: "… a Trump presidency could have a negative impact on the price of Australian agricultural commodities like beef, grain and fiber." Our result is also consistent with Huang et al. (2015), who show that U.S. elections have a substantial impact on international equity markets.

Based on the same arguments, countries outside the U.S. typically have smaller economies and less political power, which suggests that their elections may only influence their local economies instead of those of other countries. Since most commodities have global demand and supply through real trade, a non-U.S. local political shock could be diversified away through imports/exports from other countries. Therefore, it is difficult for non-U.S. elections to play a substantial role in determining commodity prices.[8]

[8] China can influence commodity prices over the last decade due to its large demand for commodity imports. However, there are only two elections during that period, which makes it difficult to find a strong statistical effect.

Turing to other coefficients, Table 1 shows that the coefficient on the pre-election year dummy DY_t is insignificant in all regressions. On the other hand, there is a positive and significant coefficient on the seasonality dummy DQ_t defined over one quarter prior to U.S. Election Day, which suggests that global commodity prices tend to increase during that one-quarter period every year. Subsequent analysis (Table 5) shows that this result is mainly caused by price increases in Energy and Green Seeds, as hot weather in the summer causes a surge in energy demand and therefore price increases, and temporary shortages of green seeds before harvest push up prices of green seeds. Consistent with past findings in the literature, the coefficient on the change of basis is positive and significant and the coefficient on the equity index return is positive and significant. The coefficient on the change of interest rates is significantly positive, which contradicts the finding of Frankel (2008), but is consistent with the results in Gorton and Rouwenhorst (2006) and Tang and Xiong (2012).

Overall, the baseline regression results suggest that political uncertainty surrounding national elections plays an important role in determining global commodity prices. In particular, U.S. presidential elections have a much stronger negative impact on global commodity prices than national elections in other countries. We also note that much of the price impact of political uncertainty is concentrated in one quarter prior to elections.[9] This is consistent with Jens (2016), who finds that firms start delaying their investment *one* quarter before U.S. gubernatorial elections.

3.2 Variation across Subsamples

In this subsection, we examine the variation of our baseline results across countries and commodity categories.

3.2.1 Different Countries

We perform the baseline regression for each of the 12 countries separately and report the results for U.S. elections and each country's own national elections in Panels A and B of Table 4, respectively. Panel A shows that 11 out of 12 countries (the UAE being the only

[9] For this reason, we focus on the one-quarter period before elections in our subsequent tests.

exception) have negative DD coefficients in relation to U.S. elections, and six out of those 11 are statistically significant.[10] An F-test also strongly rejects the null hypothesis that the average DD coefficient is equal to zero. Thus, our main finding from Table 3 that U.S. presidential elections have a negative impact on commodity prices is pervasive across individual countries and not driven by a small subset of countries.

In contrast, Panel B of Table 4 shows that outside the U.S., five out of the remaining 11 countries have negative DD coefficients in relation to local elections, whereas five others have positive coefficients (we do not estimate the regression for the UAE because it does not hold elections). Only Canada produces a statistically significant coefficient, and the F-test fails to reject the null that the average coefficient across countries is equal to zero. These results again confirm our baseline finding from Table 3 that non-U.S. national elections have a much weaker impact on commodity prices than U.S. presidential elections.

3.2.2 Different Commodity Categories

We also group commodities into five categories (Energy, Industrial Materials, Precious Metals, Green Seeds, Softs and Live Cattle) and estimate the baseline regression for each commodity category separately. Table 5 reports the results.

Panel A of Table 5 reports the results based on U.S. elections for all (U.S. and non-U.S.) commodities. The DD coefficient is negative for each of the five commodity categories and statistically significant for three out of five categories (Industrial Materials, Precious Metals, and Green Seeds).[11] The F-test also strongly rejects the null that the average coefficient across categories is zero. These results show that the negative impact of U.S. elections on global commodity prices is robust across commodity categories.

Note that the coefficient on the seasonality dummy DQ_t is positive and highly significant for both Energy and Green Seeds. Because most of countries in this study are from the Northern Hemisphere, they tend to have similar seasons. The demand for energy

[10] The six countries where the effect is significant consist of four developed countries (the U.S., France, the U.K., and Japan) and two developing countries (Malaysia and South Africa).

[11] The negative coefficient for Precious Metals is particularly interesting as it suggests that precious metals are not a hedge against political uncertainty. Consistent with this result, Huang (2015) shows that gold prices tend to fall during recessions when economic uncertainty is at the highest level.

commodities generally increases in the summer due to hot weather, causing prices to increase. In addition, the period from August to October is typically right before harvest, which is associated with a lack supply of green seeds. Hence, prices of green seeds tend to increase during this period.

Panels B and C reports the results based on U.S. elections but for U.S. (Panel B) and non-U.S. commodities (Panel C) separately. The DD coefficient is negative in all ten regressions, and is statistically significant in four of them. The F-test strongly rejects the null that the average coefficient is equal to zero for both U.S. and non-U.S. commodities. Therefore, the prices of all commodity categories fall before U.S. elections regardless where the commodities are traded.

As for the impact of non-U.S. national elections on different non-U.S. commodity prices, Panel D of Table 5 report positive DD coefficients for Energy and Precious Metals but negative coefficients for Industrial Materials, Green Seeds, and Softs and Live Cattle. None of the coefficient is statistically significant and the F-test fails to reject the null that the average coefficient across categories is zero. Hence, the weak effect of non-U.S. national elections on local commodity prices is robust across commodity categories.

3.3 Commodity Market Integration

Does the price impact of political uncertainty depend on the degree of commodity market integration? To answer this question, we classify commodities in each country into local and global commodities based on their return correlations with an equal-weighted international commodity market index representing all 87 commodities. We define local commodities as the ones whose return correlations with the commodity market index fall in the bottom tercile among all commodities traded in a given country, and the rest of the commodities in that country as global commodities.[12] We exclude each commodity from the commodity market index when calculating their return correlation. In addition, we compute all correlations over the common sample period from January 2010 to February 2017 to make them comparable.

[12] We exclude Canada, Malaysia, the UAE, and Singapore from the analysis because they each have less than three commodities traded.

We hypothesize that local commodities are more sensitive to local political uncertainty and less sensitive to global uncertainty, whereas global commodities should behave in the opposite manner. To test this hypothesis, we introduce a local commodity dummy LC and estimate the following difference-in-difference-in-difference (DDD) regression:

$$R_{i,j,t} = b_1 DQ_t + b_2 DY_t + b_3 LC + b_4 DQ_t \times DY_t + b_5 DQ_t \times LC + b_6 DY_t \times LC + b_7 DQ_t \times DY_t \times LC + controls. \quad (4)$$

The coefficient on the triple-interaction term $DQ_t \times DY_t \times LC$ captures the differential effects of U.S. or non-U.S. national elections on local vs. global commodities. Consistent with our hypothesis, the first regression in Table 6 shows a positive and significant DDD coefficient for U.S. elections, suggesting that local commodities experience a smaller price decline than global commodities prior to U.S. presidential elections. The magnitude of the effect, 4.6% ($0.353\% \times 13$), is economically large and indicates that the overall decline of 6.4% for all commodities prior to U.S. elections (Table 3) is largely driven by the global commodities within each country. The next two regressions in Table 6 show that the above result holds for both commodities traded in the U.S. and outside the U.S. Also consistent with our hypothesis, the last regression in Table 6 shows a negative DDD coefficient for non-U.S. national elections, suggesting that local commodities experience a bigger price decline than global commodities before local national elections. However, the effect is not statistically significant. Overall, the results in Table 6 provide support to our hypothesis that local commodities which are segmented from the global commodity markets are less sensitive to global political uncertainty proxied by U.S. presidential elections.

3.4 Election Closeness

We expect close elections to have a bigger impact on commodity prices as close elections are usually associated with higher degrees of political uncertainty. To test this hypothesis, we use historical polling data from the Gallup Organization to measure the closeness of U.S. presidential elections.[13] Specifically, we calculate the average polls for both the Democratic

[13] The data are publicly available online at https://en.wikipedia.org/wiki/Historical_polling_for_United_States_presidential_elections.

and Republican candidates during the quarter before each election. Our first measure of election closeness is a dummy variable which is set to one when the absolute difference between the two candidates' average polls is less than its average value (10%) and zero otherwise. Our second measure is a continuous variable which is equal to the negative value of the absolute difference between the two candidates' average polls. Panel A of Table 7 reports the two election closeness measures for the past 15 U.S. presidential elections from 1960 to 2016. Eight elections (including the recent five elections from 2000 to 2016) are classified as close elections based on the 10% absolute difference cutoff. The average absolute difference in polls is 2.6% for close elections and 18.7% for elections that are not close.

We then estimate the following DDD regressions:

$$R_{i,j,t} = b_1 DQ_t + b_2 DY_t + b_3 EC_t + b_4 DQ_t \times DY_t + b_5 DQ_t \times EC_t + b_6 DY_t \times EC_t + b_7 DQ_t \times DY_t \times EC_t + controls, \quad (5)$$

where EC_t represents either election closeness measure. The coefficient on the triple-interaction term $DQ_t \times DY_t \times EC_t$ thus captures the marginal effect of close elections on commodity prices. Panel B of Table 7 report the results of estimating Equation (5) using both election closeness measures. Consistent with our hypothesis, the first two regressions show that both DDD coefficients are negative and significant for all commodities, suggesting that close elections are associated with a more negative price impact than elections that are not close. The economic magnitude of the effect is also fairly large. The first regression shows that commodity prices on average drop by 10.3% (0.791% $\times$ 13) more prior to close elections based on the 10% cutoff. The second regression shows that a 1% decrease in the absolute difference in pools is associated with a 0.46% ($3.5\% \times 13 \times 1\%$) extra price decline in commodities prior to an election. The next four regressions show that the above DDD results are driven by U.S. commodities, whereas the price impact on non-U.S. commodities does not depend on the closeness of U.S. elections. For example, the third regression shows that U.S. commodity prices drop by 12.7% (0.976% $\times$ 13) more prior to close elections. By contrast, the fifth regression shows that non-U.S. commodity prices only drop by 1.6% (0.123% $\times$ 13) more before close elections. Overall, our results are consistent with the finding in Jens (2016) that firm investment experiences a much larger decline before close elections, which could potentially contributes to the bigger drop in (U.S.) commodity prices before those elections.

3.5 Business Cycles

Pastor and Veronesi (2013) argue that political uncertainty tends to have a stronger price impact in a recession as governments are more likely to adopt new policies such as subsidies and new tax codes. In this subsection, we study how the price impact of political uncertainty varies with business cycles. We use two business cycle proxies: a NBER recession dummy and the negative value of the Chicago Fed National Activity Index (CFNAI) developed by the Chicago Fed. We then estimate the following DDD regression:

$$R_{i,j,t} = b_0 + b_1 DQ_t + b_2 DY_t + b_3 RC_t + b_4 DQ_t \times DY_t + b_5 DQ_t \times RC_t + b_6 DY_t \times RC_t + b_7 DQ_t \times DY_t \times RC_t + controls, \quad (6)$$

where RC_t represents either business cycle proxy. Note that since the CFNAI becomes first available at the end of 1967, our regressions start in January 1968. Similar to the interpretations of the previous DDD regressions, the coefficient on the triple-interaction term $DQ_t \times DY_t \times RC_t$ in Equation (6) measures the marginal effect of business cycles on the commodity price declines before elections.

Table 8 shows that both DDD coefficients are negative and statistically highly significant for all commodities, U.S. commodities, and non-U.S. commodities. Specifically, prices on average decline by 9.8% ($0.752\% \times 13$) more prior to elections during recessions than during expansions for all commodities, 9.7% ($0.749\% \times 13$) more for U.S. commodities, and 8.6% ($0.663\% \times 13$) more for non-U.S. commodities. In addition, a 1% decrease in the CFNAI (signaling a weakening of the economy) is associated with an additional 0.31% ($2.421\% \times 13 \times 1\%$) decline in prices before an election for all commodities, 0.33% ($2.515\% \times 13 \times 1\%$) for U.S. commodities, and 0.29% ($2.213\% \times 13 \times 1\%$) for non-U.S. commodities. Therefore, recessions appear to exacerbate the negative impact of political uncertainty on worldwide commodity prices, possibly due to the dampening effect of new government policies on commodity demand.

3.6 Post-Election Commodity Prices

The analysis so far focuses on the commodity price behavior right before elections when political uncertainty is at the highest level. One natural question to ask is whether the pre-election decline in commodity prices reverses after the elections as political uncertainty gets resolved. To answer this question, we construct post-election year and seasonality dummies DAY_t and DAQ_t and introduce them to the following DD regression:

$$R_{i,j,t} = b_1 DAQ_t + b_2 DAY_t + b_3 DAQ_t \times DAY_t + controls, \qquad (7)$$

where DAY_t is set to one when week t falls into the one-year period after an election and zero otherwise, and DAQ_t is set to one when week t falls into the one- or two-quarter period after the election day in a given year and zero otherwise. The control variables are identical to those in the pre-election DD regression. The coefficient on the cross term $DAQ_t \times DAY_t$ captures the effect of low political uncertainty on commodity prices during the post-election period (one or two quarters).

We estimate Equation (7) for both U.S. and non-U.S. national elections and for both U.S. and non-U.S. commodities and report the results in Table 9. The main finding from Table 9 is that the DD coefficient is economically small and statistically insignificant in all specifications, especially for those based on U.S. presidential elections. Therefore, commodity prices do not appear to rebound after the elections. This could be due to the fact that even after a new president is elected, significant uncertainty remains about when and how the new president's policies will be implemented. Our results are also consistent with the pattern of firm investments documented by Julio and Yook (2012) and Jens (2016). Julio and Yook (2012) show that firms reduce investments during the pre-election period much more than they increase investments after elections. Jens (2016) shows that the investment level one year after an election is still lower than level before the pre-election decline in investments. The lack of post-election price rebound could therefore be tied to sluggish demand as a result of firms' investment decisions after the elections.

4. Additional Robustness Checks

4.1 More Control Variables

To ensure that our main results are not driven by omitted explanatory variables, we add more control variables to our baseline regression. Cheng, Kirilenko and Xiong (2014) show that changes in VIX have a strong negative correlation with commodity price changes during the recent financial crisis, likely due to the convective risk flow induced by the greater distress of financial institutions. Tang and Xiong (2012) show a strong negative correlation between commodity returns and USD index returns. Kilian (2009) shows that the BDI index, which is a proxy for the component of global economic activity that drives commodity demand, is a key driver of energy prices. We include the above variables as additional controls in the baseline regression and re-estimate it over the sample period from January 1990 to February 2017. The shorter sample period is due to the fact that the additional controls only become available in the late 1980s.

Panel A of Table 10 shows that the three additional control variables have strong explanatory power for commodity returns, and both the directions and magnitudes of the effects are in line with the original studies. It is also worth noting that both U.S. and non-U.S. commodities have significant exposures to the two U.S.-based control variables (VIX and USD indices), which again confirms the importance of U.S. economy in shaping worldwide commodity markets. More importantly, even with additional controls, U.S. political uncertainty still has a significant negative impact on global commodity prices. Specifically, the average price decline is 5.6% ($0.429\% \times 13$) for all commodities prior to U.S. elections, 4.9% ($0.375\% \times 13$) for U.S. commodities, and 6.1% ($0.472\% \times 13$) for non-U.S. commodities. Finally, non-U.S. national elections continue to have an insignificant effect on non-U.S. commodity prices. These results show that our main findings are not driven by omitted explanatory variables.

4.2 Nearby Futures Prices

For our main analysis, we follow the convention in the literature (Pindyck, 2001) and use commodity spot prices inferred from the prices of the nearby and second nearby futures contracts. Alternatively, Fama and French (1987) and Litzenberger and Rabinowitz (1995) directly use the nearby futures price as the proxy for spot price. Panel C of Table 10 reruns the baseline regression using spot prices obtained under this alternative method.

The results from Panel B are very close to those reported in Table 3 based on the benchmark construction of spot prices. In particular, prices on average drop by 6.0% ($0.461\% \times 13$) one quarter prior to U.S. elections for all commodities, 4.2% ($0.320\% \times 13$) for U.S. commodities, and 8.2% ($0.630\% \times 13$) for non-U.S. commodities, compared with corresponding price declines of 6.4%, 4.6%, and 8.6% as reported in Table 3. Therefore, our main results are robust to alternative methods of calculating commodity spot prices.

4.3 Endogeneity of Election Timing

As argued before, the timing of elections is important for studying the impact of political uncertainty on asset prices. In countries where the election calendar is not fixed (typically with a parliamentary system), the incumbent can call an election earlier than expected to seize upon a favorable electoral opportunity, and this typically happens during economic booms as shown by Ito (1990). In other words, the timing of an early election can be driven by strong economic activities with increasing commodity demand and rising prices, which raises the question of endogeneity. Among the 12 countries we study, the U.K., Japan, India, Malaysia, Canada, South Africa, and Singapore allow for early elections. Hence, endogeneity can be a concern about the results involving the elections in those countries. Note that our main analysis focuses on U.S. presidential elections with fixed dates (instituted by the Congress in 1845), and therefore is not affected by this endogeneity issue.

To address the endogeneity concern about the results based on non-U.S. national elections, we reestimate the baseline regression for non-U.S. commodities separately for countries with endogenous election timings and countries with exogenous election timings. The results, reported in Panel C of Table 10, show that commodity prices on average decrease by 1.3% ($0.098\% \times 13$) in one quarter prior to elections in countries with endogenous timings, and by 0.1% ($0.005\% \times 13$) in countries with exogenous timings. However, the magnitudes of both effects are very small and neither one is statistically significant. In sum, our baseline finding regarding the weak effect of non-U.S. elections on non-U.S. commodity prices is robust to controlling for endogenous timings of local elections.

5 Conclusions

In this paper, we study the impact of political uncertainty on commodity prices using a comprehensive sample of 87 commodities traded in 12 countries. Our main finding is that political uncertainty associated with U.S. presidential elections has a negative and significant impact on worldwide commodity prices, with prices falling by more than 6% during one quarter prior to elections. This result is robust across different countries and categories of commodity, and is stronger for commodities that are integrated with the global commodity markets, for close elections, and for elections during recession periods. In addition, we find that non-U.S. national elections have an insignificant impact on those countries' commodity prices. Overall, our findings are consistent with the hypothesis that demand for commodities decreases during periods of high political uncertainty, causing their prices to drop. They also highlight the importance of U.S. presidential elections in influencing worldwide commodity prices.

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Table 1: Summary Statistics of Worldwide Commodities

This table presents the summary statistics of 87 commodities traded in 12 countries. For 80 of the 87 commodities, their futures prices are obtained from the Commodity Research Bureau (CRB). For the remaining 7 commodities (copper, aluminum, aluminum alloy, lead, nickel, zinc, and Tin) traded on LME, their prices are obtained from Datastream. The final sample consists of 116,302 commodity/week observations from January 8, 1960 to February 7, 2017. The detailed description of each commodity contract is provided in the Appendix. Spot prices are directly available for the seven metals traded on the LME. For the remaining 80 commodities whose spot prices are not directly available, we follow Pindyck (2001) and back out spot prices through a linear interpolation of log prices of nearby and second nearby futures contracts. In addition, we calculate the (annualized) log basis using the nearby and second nearby futures prices. Panel A reports the summary statistics of spot commodity returns and bases for the 12 countries. Panel B reports the summary statistics for five commodity categories: Energy (11 commodities), Industrial Materials (20), Precious Metals (7), Green Seeds (34), and Softs and Live Cattle (15). Panel C reports the summary statistics of stock market index returns and interest rates (obtained from Datastream and Bloomberg) for the 12 countries.

Panel A: Commodities Prices across Countries

Countries	Number of Commodities	Exchanges	Starting Date	Weekly Spot Returns Mean (%)	Weekly Spot Returns Std Dev (%)	Basis Mean (%)	Basis Std Dev (%)
U.S.	30	New York Mercantile Exchange (NYMEX), Chicago Board of Trade (CBOT), Chicago Mercantile Exchange (CME), Minneapolis Grain Exchange (MGEX), Intercontinental Exchange (ICE)	01/05/1960	0.157	4.61	2.469	26.89
France	3	EURONEXT	10/28/1994	0.090	3.52	0.924	17.28
China	11	Shanghai Futures Exchange (SHFE), China Zhengzhou Commodity Exchange (CZCE), Dalian Commodity Exchange (DCE)	05/08/2002	0.096	3.46	0.628	23.17
U.K.	14	London International Financial Futures and Options Exchange (LIFFE), London Metal Exchange (LME) International Petroleum Exchange (IPE)	01/04/1986	0.187	5.19	2.927	32.44
Japan	9	Tokyo Commodity Exchange (TOCOM)	12/21/1992	0.167	4.67	-0.150	24.73
Brazil	3	Brazilian Mercantile and Futures Exchange (BMF)	05/22/2006	0.172	3.86	2.793	21.50
India	7	National Commodity & Derivatives Exchange (NCDEX)	04/19/2004	0.216	4.36	8.850	29.41
UAE	1	Dubai Mercantile Exchange(DME)	06/01/2007	0.094	4.93	3.387	11.15
Canada	1	Winnipeg Commodity Exchange (WCE)	09/03/1974	0.055	3.76	2.941	22.47
Malaysia	1	Malaysia Derivatives Exchange (MDEX)	01/04/2004	0.190	3.47	-3.055	18.10
South Africa	5	South African Futures Exchange (SAFEX)	01/01/2004	0.231	4.19	3.407	28.59
Singapore	2	Singapore Exchange(SGX)	01/03/2007	0.163	4.78	-0.711	16.53
average	7			0.152	4.23	2.034	22.69

Panel B: Commodity Prices across Categories

Groups	Spot Returns Mean (%)	Spot Returns Std Dev (%)	Basis Mean (%)	Basis Std Dev (%)
Energy	0.301	6.94	2.573	48.44
Industrial Materials	0.133	4.15	2.004	18.30
Precious Metals	0.164	3.83	1.925	6.91
Green Seeds	0.136	4.06	2.622	23.97
Softs and Live Cattle	0.151	4.60	2.077	29.36

Panel C: Stock Market Returns and Interest Rates across Countries

Countries	Average stock market index returns (annualized)	Std dev stock market index returns (annualized)	Average interest rate	Std dev interest rate
U.S.	7.6	15.4	5.1	3.1
France	6.2	20.9	3.6	3.0
China	10.1	26.7	2.6	0.8
U.K.	7.3	16.9	3.6	2.5
Japan	6.3	19.2	0.2	0.3
Brazil	75.4	63.4	11.4	2.1
India	17.5	25.1	6.9	1.6
UAE	11.1	20.3	2.5	1.7
Canada	7.1	15.3	3.0	2.0
Malaysia	9.4	21.1	3.0	0.4
South Africa	12.7	21.0	8.1	1.9
Singapore	3.8	19.0	1.2	0.9

Table 2: Summary Statistics of National Elections and Political Systems

We obtain the national election data from Polity IV Project, conducted by the Center for Systemic Peace and Conflict Management at the University of Maryland, over the 1960-2017 sample period. We further compare our data with data from the World Bank Political Institution database and correct erroneous or missing data with various online sources. Note that the UAE does not hold national elections but instead follow a system of a federal, presidential, and absolute monarchy.

Countries	Starting Date	Number of Elections	Basis of Executive Legitimacy	Election Timing
U.S.	01/05/1960	15	Presidential	Fixed
France	10/28/1994	4	Hybrid	Fixed
China	05/08/2002	2	Hierarchical	Fixed
U.K.	01/04/1986	7	Parliamentary	Flexible
Japan	12/21/1992	9	Parliamentary	Flexible
Brazil	05/22/2006	3	Presidential	Fixed
India	04/19/2004	3	Parliamentary	Flexible
UAE	NA	NA	NA	NA
Canada	09/03/1974	13	Parliamentary	Flexible
Malaysia	01/04/2004	3	Parliamentary	Flexible
South Africa	01/01/2004	3	Parliamentary	Flexible
Singapore	01/03/2007	2	Parliamentary	Flexible

Table 3: Political Uncertainty and Commodity Prices, the Baseline Regression

Table 3 reports the results from estimating the following difference-in-difference (DD) regression over the sample period from January 8, 1960 to February 7, 2017:

$$R_{i,j,t} = b_0 + b_1 DQ_t + b_2 DY_t + b_3 DQ_t \times DY_t + b_4 \Delta B_{i,j,t} + b_5 R^e_{j,t} + b_6 \Delta I_{j,t} + \sum_{k=1}^{52} c_k R_{i,j,t-k} + u_i + \varepsilon_{i,j,t},$$

where the dependent variable $R_{i,j,t}$ is the arithmetic spot return of commodity *i* from country *j* in week *t*. The explanatory variable DQ_t is equal to one when week *t* falls into the one- or two-quarter period before the election in a given year and zero otherwise, and DY_t is equal to one when week *t* falls into the one-year period leading up to an election and zero otherwise. The control variables are as follows: $\Delta B_{i,j,t}$ is the change in basis, $R^e_{j,t}$ is the return of the equity market index in country j, $\Delta I_{j,t}$ is the interest rate change in country j, $R_{i,j,t-k}$ is the commodity return in week *t*-*k*, and u_i captures the commodity-fixed effect. Reported are the regression coefficient estimates and their associated *t*-statistics computed based on the double-clustering standard errors as in Petersen (2009). *,** and *** represent significance at the 10%, 5% and 1% levels, respectively. For brevity, the coefficients and *t*-statistics of lagged commodity returns and commodity fixed effects are not reported.

Panel A: One Quarter Pre-Election as Periods of High Political Uncertainty

Coefficients($\times \mathbf{100}$)	U.S. Elections All Commodities		U.S. Elections U.S. Commodities		U.S. Elections Non-U.S. Commodities		Non-U.S. Elections Non-U.S. Commodities	
$DQ_t \times DY_t$	-0.483**	-0.494***	-0.314*	-0.355**	-0.701**	-0.658***	-0.092	-0.080
	(-2.25)	(-2.64)	(-1.65)	(-2.08)	(-2.54)	(-2.82)	(-0.63)	(-0.59)
DQ_t	0.056	0.168**	0.010	0.166*	0.119	0.166	0.017	0.029
	(0.48)	(2.01)	(0.07)	(1.68)	(0.76)	(1.62)	(0.14)	(0.33)
DY_t	0.045	0.085	0.032	0.044	0.063	0.146	0.011	-0.012
	(0.53)	(1.04)	(0.36)	(0.52)	(0.61)	(1.47)	(0.16)	(-0.16)
$\Delta B_{i,j,t}$		-18.062***		-18.427***		-17.644***		-17.647***
		(-10.74)		(-5.96)		(-13.84)		(-13.83)
$R^e_{j,t}$		17.289***		15.422***		18.443***		18.463***
		(7.60)		(5.87)		(6.83)		(6.69)
$\Delta I_{j,t}$		0.448*		0.138		1.594***		1.616***
		(1.86)		(0.59)		(3.28)		(3.28)
Fixed Effect	No	Yes	No	Yes	No	Yes	No	Yes
$\mathbf{R^2}$	0.05%	31.36%	0.02%	29.00%	0.11%	34.94%	0.01%	34.86%
No. of Obs.	116302	116302	66638	66638	49664	49664	49664	49664
Start. Year	1960	1960	1960	1960	1974	1974	1974	1974

Panel B: Two Quarters Pre-Election as Periods of High Political Uncertainty

Coefficients($\times 100$)	U.S. Elections All Commodities		U.S. Elections U.S. Commodities		U.S. Elections Non-U.S. Commodities		Non-U.S. Elections Non-U.S. Commodities	
$DQ_t \times DY_t$	-0.306*	-0.306**	-0.275*	-0.279*	-0.345*	-0.325*	0.033	-0.006
	(-1.89)	(-2.04)	(-1.76)	(-1.91)	(-1.70)	(-1.76)	(0.22)	(-0.05)
DQ_t	-0.094	0.016	-0.085	-0.002	-0.107	0.028	0.096	0.029
	(-1.10)	(0.20)	(-0.86)	(-0.02)	(-0.97)	(0.26)	(0.97)	(0.31)
DY_t	0.078	0.114	0.091	0.095	0.059	0.142	-0.040	-0.030
	(0.75)	(1.19)	(0.88)	(0.97)	(0.47)	(1.22)	(-0.40)	(-0.31)
$\Delta B_{i,j,t}$		-18.059***		-18.418***		-17.646***		-17.647***
		(-10.74)		(-5.96)		(-13.82)		(-13.82)
$R^e_{j,t}$		17.195***		15.281***		18.385***		18.448***
		(7.50)		(5.81)		(6.75)		(6.70)
$\Delta I_{j,t}$		0.430*		0.118		1.601***		1.618***
		(1.78)		(0.50)		(3.28)		(3.29)
Fixed Effect	No	Yes	No	Yes	No	Yes	No	Yes
$\mathbf{R^2}$	0.06%	31.34%	0.05%	28.99%	0.09%	34.89%	0.01%	34.86%
No. of Obs.	116302	116302	66638	66638	49664	49664	49664	49664
Start. Year	1960	1960	1960	1960	1974	1974	1974	1974

Table 4: Political Uncertainty and Commodity Prices, Individual Countries

Table 4 reports the results from estimating the baseline DD regression for each of the 12 countries separately over the sample period from January 8, 1960 to February 7, 2017. Panel A reports the results based on U.S. elections. Panel B reports the results based on non-U.S. national elections. Note that the UAE has no national elections due to its political system. Reported are the regression coefficient estimates and their associated t-statistics computed based on the double-clustering standard errors as in Petersen (2009). *,** and *** represent significance at the 10%, 5% and 1% levels, respectively. For brevity, the coefficients and t-statistics of lagged commodity returns and commodity fixed effects are not reported.

Panel A: Political Uncertainty Measured by U.S. Elections

Coefficients($\times$ $\mathbf{100}$)	U.S.	France	China	U.K.	Japan	Brazil
$\boldsymbol{DQ_t \times DY_t}$	-0.355**	-0.473**	-0.500	-0.526**	-0.830***	-0.790
	(-2.08)	(-2.09)	(-1.40)	(-1.97)	(-2.69)	(-1.44)
$\boldsymbol{DQ_t}$	0.166*	0.365**	0.066	0.151	0.052	0.464*
	(1.68)	(2.03)	(0.43)	(1.13)	(0.34)	(1.76)
$\boldsymbol{DY_t}$	0.044	-0.068	0.191	0.148	0.118	0.175
	(0.52)	(-0.42)	(1.21)	(1.25)	(0.81)	(0.76)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	29.00%	42.59%	31.40%	43.90%	35.24%	22.84%
No. of Obs.	66638	2663	6297	18558	10080	1663
Starting Year	1960	1994	2002	1986	1992	1999
Coefficients($\times$ $\mathbf{100}$)	**India**	**UAE**	**Canada**	**Malaysia**	**South Africa**	**Singapore**
$\boldsymbol{DQ_t \times DY_t}$	-0.696	0.230	-0.323	-1.477*	-0.952**	-0.719
	(-1.17)	(0.24)	(-0.91)	(-1.79)	(-2.52)	(-0.98)
$\boldsymbol{DQ_t}$	-0.054	-0.075	0.191	0.563**	0.546**	0.135
	(-0.17)	(-0.20)	(1.47)	(2.00)	(2.18)	(0.37)
$\boldsymbol{DY_t}$	0.150	-0.357	0.161	0.026	0.187	0.382
	(0.47)	(-0.69)	(0.98)	(0.11)	(0.72)	(1.28)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	26.38%	42.06%	41%	22%	38.13%	38.98%
No. of Obs.	2971	452	2160	734	3140	946
Starting Year	2006	2007	1974	2002	2004	2007
F-test of zero average DD coefficient: 25.12* **						

Panel B: Political Uncertainty Measured by Non-U.S. National Elections

Coefficients($\times$ 100)	U.S.	France	China	U.K.	Japan	Brazil
$DQ_t \times DY_t$	-0.355**	-0.049	0.048	-0.193	0.324	0.332
	(-2.08)	(-0.16)	(0.17)	(-0.85)	(1.24)	(0.80)
DQ_t	0.166*	-0.271	0.122	0.174	-0.145	0.004
	(1.68)	(-1.48)	(0.58)	(1.42)	(-0.76)	(0.04)
DY_t	0.044	0.204	-0.262	0.083	-0.218	0.428***
	(0.52)	(1.27)	(-1.31)	(0.64)	(-1.44)	(3.71)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	29.00%	42.51%	31.38%	43.88%	35.14%	22.94%
No. of Obs.	66638	2663	6297	18558	10080	1663
Starting Year	1960	1994	2002	1986	1992	1999
Coefficients($\times$ 100)	**India**	**UAE**	**Canada**	**Malaysia**	**South Africa**	**Singapore**
$DQ_t \times DY_t$	0.433	NA	-1.292***	0.651	-0.805	-0.954
	(0.87)	NA	(-3.66)	(0.87)	(-1.54)	(-1.30)
DQ_t	0.321	NA	0.140	-0.012	-0.317	-0.862***
	(1.05)	NA	(0.83)	(-0.04)	(-1.06)	(-2.90)
DY_t	-0.103	NA	0.446	0.045	-0.230	0.292
	(-0.35)	NA	(3.04)	(0.14)	(-0.82)	(0.95)
Controls	Yes	NA	Yes	Yes	Yes	Yes
Fixed Effect	Yes	NA	Yes	Yes	Yes	Yes
R^2	26.40%	NA	41.58%	21.47%	38.30%	39.71%
No. of Obs.	2971	452	2160	734	3140	946
Starting Year	2006	2007	1974	2002	2004	2007

F-test of zero average DD coefficient: 2.24

Table 5: Political Uncertainty and Commodity Prices, Individual Categories

Table 5 reports the results from estimating the baseline DD regression for each of the five commodity categories separately over the sample period from January 8, 1960 to February 7, 2017. Reported are the regression coefficient estimates and their associated *t*-statistics computed based on the double-clustering standard errors as in Petersen (2009). *,** and *** represent significance at the 10%, 5% and 1% levels, respectively. For brevity, the coefficients and *t*-statistics of lagged commodity returns and commodity fixed effects are not reported.

Panel A: All Commodities and U.S. Elections

Coefficients($\times$ 100)	Energy	Industrial Materials	Precious Metals	Green Seeds	Softs and Live Cattle
$DQ_t \times DY_t$	-0.405	-0.459*	-0.798***	-0.583***	-0.211
	(-0.94)	(-1.68)	(-2.58)	(-2.61)	(-1.27)
DQ_t	0.470**	0.031	0.087	0.286***	-0.026
	(2.20)	(0.26)	(0.58)	(2.73)	(-0.20)
DY_t	0.248	0.056	0.124	0.111	-0.017
	(1.18)	(0.46)	(0.82)	(1.03)	(-0.19)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	55.74%	23.97%	8.74%	31.12%	21.75%
No. of Obs.	13178	23573	12272	42496	24783
Staring Year	1978	1960	1973	1960	1960
F-test of zero average DD coefficient: 65.62* **					

Panel B: U.S. Commodities and U.S. Elections

Coefficients($\times 100$)	Energy	Industrial Materials	Precious Metals	Green Seeds	Softs and Live Cattle
$DQ_t \times DY_t$	-0.451	-0.030	-0.804***	-0.333	-0.185
	(-1.19)	(-0.20)	(-2.62)	(-1.42)	(-1.15)
DQ_t	0.552**	-0.029	0.171	0.297**	-0.027
	(2.41)	(-0.40)	(1.17)	(2.27)	(-0.18)
DY_t	0.269	-0.129	0.141	0.060	-0.056
	(1.31)	(-1.32)	(0.87)	(0.51)	(-0.63)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	54.71%	37.83%	8.95%	25.02%	24.56%
No. of Obs.	7192	7390	8537	23892	19627
Staring Year	1978	1960	1973	1960	1961
F-test of zero average DD coefficient: 18.59* **					

Panel C: Non-U.S. Commodities and U.S. Elections

Coefficients($\times 100$)	Energy	Industrial Materials	Precious Metals	Green Seeds	Softs and Live Cattle
$DQ_t \times DY_t$	-0.358	-0.612*	-0.786**	-0.884***	-0.338
	(-0.77)	(-1.90)	(-2.18)	(-3.36)	(-1.32)
DQ_t	0.362	0.053	-0.100	0.302***	-0.028
	(1.62)	(0.36)	(-0.58)	(2.58)	(-0.19)
DY_t	0.219	0.132	0.066	0.166	0.147
	(0.98)	(0.94)	(0.43)	(1.27)	(1.01)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	58.40%	18.96%	14.40%	39.09%	24.27%
No. of Obs.	5986	16183	3735	18604	5156
Staring Year	1986	1986	1992	1977	1960
F-test of zero average DD coefficient: 43.31* **					

Panel D: Non-U.S. Commodities and Non-U.S. Elections

Coefficients($\times$ 100)	Energy	Industrial Materials	Precious Metals	Green Seeds	Softs and Live Cattle
$DQ_t \times DY_t$	0.298	-0.162	0.418	-0.110	-0.289
	(0.85)	(-0.73)	(1.21)	(-0.52)	(-1.34)
DQ_t	0.100	0.103	-0.322	-0.053	0.043
	(0.45)	(0.68)	(-1.18)	(-0.51)	(0.39)
DY_t	-0.150	-0.030	-0.131	-0.002	0.192
	(-0.68)	(-0.26)	(-0.85)	(-0.02)	(1.60)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	58.38%	18.88%	14.19%	38.94%	24.25%
No. of Obs.	5986	16183	3735	18604	5156
Staring Year	1986	1986	1992	1977	1960
F-test of zero average DD coefficient: 0.08					

Table 6: Political Uncertainty, Commodity Prices, and Market Integration

Table 6 reports the results from estimating the following difference-in-difference-in-difference (DDD) regression over the sample period from January 8, 1960 to February 7, 2017:

$$R_{i,j,t} = b_0 + b_1 DQ_t + b_2 DY_t + b_3 LC + b_4 DQ_t \times DY_t + b_5 DQ_t \times LC + b_6 DY_t \times LC + b_7 DQ_t \times DY_t \times LC + controls,$$

where LC is a local commodity dummy which is equal to one if a given commodity's return correlation with the equal-weighted international commodity market index falls in the bottom tercile among all commodities traded its country. Each commodity is excluded from the commodity market index when calculating its return correlation with the market index. In addition, all correlations are computed over the common sample period from January 2010 to February 2017 to make them comparable. Canada, Malaysia, the UAE, and Singapore are excluded from the analysis because they each have less than three commodities traded. Reported are the regression coefficient estimates and their associated *t*-statistics computed based on the double-clustering standard errors as in Petersen (2009). *,** and *** represent significance at the 10%, 5% and 1% levels, respectively. For brevity, the coefficients and *t*-statistics of lagged commodity returns and commodity fixed effects are not reported.

Coefficients($\times$ $\mathbf{100}$)	All Commodities U.S. Election	U.S. Commodities U.S. Election	Non-U.S. Commodities U.S. Election	Non-U.S. Commodities Non-U.S. Elections
$\boldsymbol{DQ_t \times DY_t \times LC}$	0.353**	0.305*	0.289*	-0.085
	(2.37)	(1.87)	(1.76)	(-0.30)
$\boldsymbol{DQ_t \times DY_t}$	-0.569***	-0.439**	-0.704***	0.013
	(-2.77)	(-2.18)	(-2.98)	(0.09)
$\boldsymbol{DQ_t}$	0.196**	0.234**	0.145	0.056
	(2.19)	(2.29)	(1.40)	(0.58)
$\boldsymbol{DY_t}$	0.096	0.065	0.139	-0.078
	(1.04)	(0.66)	(1.31)	(-0.97)
$\boldsymbol{LC}$	-0.288	0.105***	-0.044	0.023
	(-0.31)	(2.76)	(-0.24)	(0.16)
$\boldsymbol{DQ_t \times LC}$	-0.136	-0.246	0.091	-0.163
	(-0.97)	(-1.52)	(0.36)	(-0.68)
$\boldsymbol{DY_t \times LC}$	-0.036	-0.076	0.114	0.219
	(-0.37)	(-0.67)	(1.11)	(1.61)
Controls	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	31.49%	29.00%	35.53%	35.46%
No. of Obs.	112010	66638	45372	45372
Starting Year	1960	1960	1986	1986

Table 7: Political Uncertainty, Commodity Prices, and Election Closeness

Historical polling data from the Gallup Organization are used to measure the closeness of U.S. presidential elections. Specifically, the average polls for both the Democratic and Republican candidates during the quarter before each election are calculated. The first measure of election closeness (Specification 1) is a dummy variable which is set to one when the absolute difference between the two candidates' average polls is less than its average value (10%) and zero otherwise. The second measure (Specification 2) is a continuous variable which is equal to the negative value of the absolute difference between the two candidates' average polls. Panel A of Table 7 reports the polling results for the past 15 presidential elections. Panel B reports the results from estimating the following difference-in-difference-in-difference (DDD) regression over the sample period from January 8, 1960 to February 7, 2017:

$$R_{i,j,t} = b_0 + b_1 DQ_t + b_2 DY_t + b_3 EC_t + b_4 DQ_t \times DY_t + b_5 DQ_t \times EC_t + b_6 DY_t \times EC_t + b_7 DQ_t \times DY_t \times EC_t + controls,$$

where EC_t represents either election closeness measure. Reported are the regression coefficients and their associated t-statistics computed based on the double-clustering standard errors as in Petersen (2009). *,** and *** represent significance at the 10%, 5% and 1% levels, respectively. For brevity, the coefficients and t-statistics of lagged commodity returns and commodity fixed effects are not reported.

Panel A: Closeness of U.S. Presidential Elections

Election Year	Average Poll (Democrat)	Average Poll (Republican)	Closeness Dummy	Negative Abs Poll Difference
1960	47%	47%	1	0%
1964	64%	30%	0	-34%
1968	31%	44%	0	-13%
1972	33%	60%	0	-27%
1976	50%	39%	0	-11%
1980	39%	40%	1	-1%
1984	39%	56%	0	-17%
1988	43%	47%	1	-4%
1992	48%	36%	0	-12%
1996	52%	36%	0	-17%
2000	45%	46%	1	-1%
2004	46%	50%	1	-4%
2008	49%	43%	1	-5%
2012	48%	46%	1	-2%
2016	43%	39%	1	-4%
Average	45%	44%	0.53	-10%

Panel B: Political Uncertainty, Commodity Prices, and Election Closeness

Coefficients($\times$ 100)	All Commodities U.S. Elections		U.S. Commodities U.S. Elections		Non-U.S. Commodities U.S. Elections	
	Specification1	Specification2	Specification1	Specification2	Specification1	Specification2
$\boldsymbol{DQ_t \times DY_t \times RC_t}$	-0.791**	-3.500**	-0.976***	-4.591***	-0.123	3.329
	(-2.49)	(-2.28)	(-3.00)	(-3.05)	(-0.32)	(1.10)
$\boldsymbol{DQ_t \times DY_t}$	0.070	-0.750***	0.227	-0.761***	-0.551*	-0.500*
	(0.36)	(-2.93)	(1.13)	(-3.01)	(-1.92)	(-1.73)
$\boldsymbol{DQ_t}$	0.055	0.199*	0.000	0.237*	0.225	0.148
	(0.48)	(1.79)	(0.00)	(1.86)	(1.38)	(1.04)
$\boldsymbol{DY_t}$	-0.155	0.215*	-0.203**	0.220*	0.039	0.188
	(-1.63)	(1.86)	(-2.05)	(1.67)	(0.28)	(1.47)
$\boldsymbol{RC_t}$	-0.017	0.240	-0.050	0.087	0.045	0.374
	(-0.24)	(1.13)	(-0.65)	(0.35)	(0.43)	(1.27)
$\boldsymbol{DQ_t \times RC_t}$	0.157	0.380	0.275*	0.800	-0.069	-0.571
	(1.06)	(0.52)	(1.77)	(1.16)	(-0.35)	(-0.40)
$\boldsymbol{DY_t \times RC_t}$	0.340**	1.730**	0.417**	1.966**	0.123	0.613
	(2.29)	(2.24)	(2.49)	(2.32)	(0.70)	(0.50)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	31.38%	31.54%	29.05%	29.10%	35.19%	35.12%
No. of Obs.	116302	113420	66638	66638	49664	49664
Starting Year	1960	1960	1960	1960	1974	1974

Table 8: Political Uncertainty, Commodity Prices, and Business Cycles

Table 8 reports the results from estimating the following difference-in-difference-in-difference (DDD) regression over the sample period from January 8, 1960 to February 7, 2017:

$$R_{i,j,t} = b_0 + b_1 DQ_t + b_2 DY_t + b_3 RC_t + b_4 DQ_t \times DY_t + b_5 DQ_t \times RC_t + b_6 DY_t \times RC_t + b_7 DQ_t \times DY_t \times RC_t + controls$$

where RC_t represents a business cycle proxy. It is set to either the NBER recession dummy (Specification 1) or the negative value of the Chicago Fed National Activity Index (CFNAI) developed by the Chicago Fed (Specification 2, starting from January 8, 1968). Reported are the regression coefficients and their associated *t*-statistics computed based on the double-clustering standard errors as in Petersen (2009). *,** and *** represent significance at the 10%, 5% and 1% levels, respectively. For brevity, the coefficients and *t*-statistics of lagged commodity returns and commodity fixed effects are not reported.

Coefficients($\times$ $\mathbf{100}$)	All Commodities U.S. Elections		U.S. Commodities U.S. Elections		Non-U.S. Commodities U.S. Elections	
	Specification1	Specification2	Specification1	Specification2	Specification1	Specification2
$\boldsymbol{DQ_t \times DY_t \times RC_t}$	-0.752***	-2.421***	-0.749***	-2.515**	-0.663*	-2.213**
	(-2.91)	(-2.60)	(-2.90)	(-2.40)	(-1.90)	(-2.26)
$\boldsymbol{DQ_t \times DY_t}$	-0.348**	-0.161	-0.368**	-0.126	-0.308	-0.221
	(-2.24)	(-1.13)	(-2.20)	(-0.89)	(-1.63)	(-1.18)
$\boldsymbol{DQ_t}$	0.155*	0.188**	0.158	0.200**	0.152	0.174*
	(1.86)	(2.21)	(1.55)	(1.97)	(1.59)	(1.71)
$\boldsymbol{DY_t}$	0.089	0.032	0.064	-0.012	0.151*	0.104
	(1.09)	(0.43)	(0.70)	(-0.15)	(1.71)	(1.15)
$\boldsymbol{RC_t}$	0.122	-0.235	0.140	-0.258	0.090	-0.223
	(1.07)	(-0.82)	(1.29)	(-0.95)	(0.51)	(-0.50)
$\boldsymbol{DQ_t \times RC_t}$	0.091	0.422	0.125	0.467	-0.048	0.297
	(0.69)	(1.10)	(1.07)	(1.22)	(-0.23)	(0.62)
$\boldsymbol{DY_t \times RC_t}$	-18.027***	-18.057***	-18.372***	-18.425***	-17.638***	-17.636***
	(-10.63)	(-10.75)	(-5.84)	(-5.96)	(-13.82)	(-13.81)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	31.54%	31.58%	29.10%	35.33%	35.12%	35.19%
No. of Obs.	113420	116302	66638	66638	49664	49664
Starting Year	1960	1960	1960	1960	1986	1986

Table 9: Post-Election Commodity Prices

Table 9 reports the results from estimating the following difference-in-difference (DD) regression over the sample period from January 8, 1960 to February 7, 2017:

$$R_{i,j,t} = b_0 + b_1 DAQ_t + b_2 DAY_t + b_3 DAQ_t \times DAY_t + controls,$$

where DAY_t is set to one when week *t* falls into the one-year period after an election and zero otherwise, and DAQ_t is set to one when week t falls into the one- or two-quarter period after the election day in a given year and zero otherwise. Reported are the regression coefficients and their associated *t*-statistics computed based on the double-clustering standard errors as in Petersen (2009). *,** and *** represent significance at the 10%, 5% and 1% levels, respectively. For brevity, the coefficients and *t*-statistics of lagged commodity returns and commodity fixed effects are not reported.

Panel A: One Quarter Post-Election

	U.S. Elections All Commodities	U.S. Elections U.S. Commodities	U.S. Elections Non-U.S. Commodities	Non-U.S. Elections Non-U.S. Commodities
$DAQ_t \times DAY_t$	-0.074	-0.049	-0.063	-0.061
	(-0.44)	(-0.30)	(-0.29)	(-0.45)
DAQ_t	0.006	0.022	-0.016	-0.001
	(0.08)	(0.25)	(-0.14)	(-0.02)
DAY_t	-0.028	-0.041	-0.016	0.028
	(-0.38)	(-0.54)	(-0.16)	(0.40)
Controls	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes
R^2	31.32%	28.97%	34.86%	34.86%
No. of Obs.	116302	66638	49664	49664
Starting Year	1960	1960	1974	1974

Panel B: Two Quarters Post-Election

	U.S. Elections All Commodities	U.S. Elections U.S. Commodities	U.S. Elections Non-U.S. Commodities	Non-U.S. Elections Non-U.S. Commodities
$\boldsymbol{DAQ_t \times DAY_t}$	-0.055	0.062	-0.199	0.065
	(-0.40)	(0.43)	(-1.11)	(0.49)
$\boldsymbol{DAQ_t}$	0.077	0.058	0.107	-0.013
	(0.99)	(0.67)	(1.09)	(-0.15)
$\boldsymbol{DAY_t}$	-0.021	-0.086	0.066	-0.019
	(-0.22)	(-0.86)	(0.53)	(-0.23)
Controls	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	31.32%	28.98%	34.88%	34.86%
No. of Obs.	116302	66638	49664	49664
Starting Year	1960	1960	1974	1974

Table 10: Additional Robustness Checks

Panel A of Table 10 reports the results from estimating the baseline DD regression with additional control variables over the sample period from January 5, 1990 to February 7, 2017. The additional control variables include the change of VIX, ΔVIX_t, the log return of USD exchange rate, R_t^{USD}, and the log return of the Baltic Dry Index, R_t^{BDI}. Panel B reports the results from estimating the baseline DD regression using the nearby futures prices as the proxy for spot prices, over the sample period from January 8, 1960 to February 7, 2017. Panel C reports the results from estimating the baseline DD regression for non-U.S. commodities separately for countries with endogenous election timings and countries with exogenous election timings, over the sample period from January 8, 1960 to February 7, 2017. Reported are the regression coefficients and their associated *t*-statistics computed based on the double-clustering standard errors as in Petersen (2009). *,** and *** represent significance at the 10%, 5% and 1% levels, respectively. For brevity, the coefficients and *t*-statistics of lagged commodity returns and commodity fixed effects are not reported.

Panel A: Baseline Regression with Additional Control Variables

Coefficients($\times$ 100)	All Commodities U.S. Elections	U.S. Commodities U.S. Elections	Non-U.S. Commodities U.S. Elections	Non-U.S. Commodities Non-U.S. Elections
$DQ_t \times DY_t$	-0.429**	-0.375*	-0.472**	-0.016
	(-2.23)	(-1.89)	(-2.25)	(-0.12)
DQ_t	0.104	0.095	0.107	-0.024
	(1.06)	(0.75)	(1.02)	(-0.27)
DY_t	0.096	0.081	0.112	-0.006
	(0.98)	(0.72)	(1.11)	(-0.09)
$\Delta B_{i,j,t}$	-17.612***	-17.684***	-17.537***	-17.539***
	(-9.23)	(-4.49)	(-13.35)	(-13.35)
$R^e_{j,t}$	13.362***	11.409***	14.133***	14.053***
	(7.26)	(3.81)	(6.66)	(6.58)
$\Delta I_{j,t}$	1.487***	1.469**	1.576***	1.591***
	(3.38)	(2.00)	(3.31)	(3.33)
R^{USD}_t	-36.577***	-47.562***	-27.458***	-27.914***
	(-8.07)	(-7.93)	(-5.56)	(-5.64)
ΔVIX_t	-0.066***	-0.064***	-0.075***	-0.076***
	(-3.87)	(-3.02)	(-3.68)	(-3.70)
R^{BDI}_t	1.233**	1.241*	1.169*	1.285**
	(1.97)	(1.67)	(1.83)	(1.96)
Fixed Effect	Yes	Yes	Yes	Yes
R^2	34.50%	33.11%	36.11%	36.07%
No. of Obs.	86455	38702	47753	47753
Staring Year	1990	1990	1990	1990

Panel B: Baseline Regression with Spot Prices Proxied by Nearby Futures Prices

Coefficients($\times \mathbf{100}$)	U.S. Elections All Commodities		U.S. Elections U.S. Commodities		U.S. Elections Non-U.S. Commodities		Non-U.S. Elections Non-U.S. Commodities	
$DQ_t \times DY_t$	-0.467**	-0.461**	-0.298	-0.320*	-0.683**	-0.630***	-0.084	-0.112
	(-2.17)	(-2.48)	(-1.57)	(-1.87)	(-2.44)	(-2.77)	(-0.58)	(-0.83)
DQ_t	0.073	0.158*	0.057	0.162*	0.096	0.161	0.055	0.048
	(0.71)	(1.88)	(0.47)	(1.72)	(0.69)	(1.48)	(0.54)	(0.58)
DY_t	0.041	0.081	0.023	0.036	0.065	0.145	0.014	-0.006
	(0.48)	(1.00)	(0.26)	(0.44)	(0.62)	(1.48)	(0.21)	(-0.09)
$\Delta B_{i,j,t}$		-9.397***		-10.702***		-7.969***		-7.971***
		(-10.38)		(-6.96)		(-8.73)		(-8.74)
$R^e_{j,t}$		17.161***		15.200***		18.297***		18.309***
		(7.74)		(5.97)		(6.86)		(6.72)
$\Delta I_{j,t}$		0.433*		0.148		1.521***		1.539***
		(1.81)		(0.63)		(3.17)		(3.17)
Fixed Effect	No	Yes	No	Yes	No	Yes	No	Yes
$\mathbf{R^2}$	0.06%	12.44%	0.22%	13.19%	0.14%	12.20%	0.00%	12.11%
No. of Obs.	116302	116302	66638	66638	49664	49664	9107	9107
Start. Year	1960	1960	1960	1960	1974	1974	1974	1974

Panel C: Baseline Regression for Non-U.S. Commodities, Endogenous vs. Exogenous Election Timing

Coefficients($\times$ 100)	Commodities in Endogenous Election Timing Countries		Commodities in Exogenous Election Timing Countries	
$DQ_t \times DY_t$	-0.095	-0.098	-0.017	-0.005
	(-0.54)	(-0.62)	(-0.09)	(-0.03)
DQ_t	-0.000	0.039	0.049	-0.007
	(-0.00)	(0.43)	(0.34)	(-0.06)
DY_t	-0.012	-0.006	0.067	0.008
	(-0.14)	(-0.08)	(0.46)	(0.05)
$\Delta B_{i,j,t}$		-18.266***		-14.436***
		(-13.36)		(-9.77)
$R^e_{j,t}$		21.387***		13.145***
		(6.32)		(4.23)
$\Delta I_{j,t}$		1.829***		0.924
		(3.38)		(1.21)
Fixed Effect	No	Yes	No	Yes
$\mathbf{R^2}$	0.00%	36.66%	0.00%	27.33%
No. of Obs.	38589	38589	11075	11075
Starting Year	1974	1974	1986	1986

Appendix: Detailed Descriptions of Commodity Contracts

Name	Exchange	Starting Date	Country	Pct no-trading dates	No. of Obs.	Category
Crude Oil, WTI / Global Spot	NYMEX	03/30/1983	US	0.0%	394	Energy
ULSD NY Harbor	NYMEX	11/14/1978	US	0.1%	446	Energy
Natural Gas, Henry Hub	NYMEX	04/04/1990	US	0.0%	309	Energy
Ethanol	CBOT	03/23/2005	US	9.9%	130	Energy
Gasoline, Blendstock	NYMEX	10/03/2005	US	1.3%	373	Energy
Coffee 'C' /Colombian	ICE	08/16/1972	US	0.1%	521	Softs and Live Cattle
Milk	CME	01/11/1996	US	5.8%	240	Softs and Live Cattle
Orange Juice	ICE	02/01/1967	US	0.3%	587	Softs and Live Cattle
Sugar #11/World Raw	ICE	01/04/1961	US	0.0%	660	Softs and Live Cattle
Sugar #16/Domestic Raw	ICE	09/26/2008	US	16.0%	87	Softs and Live Cattle
Cocoa / Ivory Coast	ICE	01/08/1960	US	1.6%	671	Softs and Live Cattle
Corn / No. 2 Yellow	CBOT	01/08/1960	US	0.0%	671	Green Seeds
Oats / No. 2 White Heavy	CBOT	01/08/1960	US	0.2%	671	Green Seeds
Rough Rice #2	CBOT	08/20/1986	US	0.1%	353	Green Seeds
Soybeans / No. 1 Yellow	CBOT	01/08/1960	US	0.0%	671	Green Seeds
Soybean Meal / 48% Protein	CBOT	01/08/1960	US	0.0%	671	Green Seeds
Soybean Oil / Crude	CBOT	01/08/1960	US	0.0%	671	Green Seeds
Wheat / No. 2 Soft Red	CBOT	01/08/1960	US	0.0%	671	Green Seeds
Wheat / No. 2 Hard Winter	CBOT	01/05/1970	US	0.0%	552	Green Seeds
Wheat / Spring 14% Protein	MGEX	01/02/1979	US	0.3%	521	Green Seeds

Cotton / 1-1/16"	ICE	01/08/1960	US	1.2%	671	Industrial Material
Lumber / Spruce-Pine Fir 2x4	CME	10/01/1969	US	0.0%	555	Industrial Material
Cattle, Feeder / Average	CME	11/30/1971	US	0.1%	529	Softs and Live Cattle
Cattle, Live / Choice Average	CME	11/30/1964	US	0.0%	614	Softs and Live Cattle
Hogs, Lean / Average Iowa/S Minn	CME	02/28/1966	US	0.0%	599	Softs and Live Cattle
Copper High Grade / Scrap No. 2 Wire	NYMEX	01/08/1960	US	0.0%	468	Industrial Material
Gold	NYMEX	12/31/1974	US	0.0%	492	Precious Metals
Palladium	NYMEX	01/03/1977	US	0.5%	468	Precious Metals
Platinum	NYMEX	03/04/1968	US	0.1%	503	Precious Metals
Silver 5,000 Troy Oz.	NYMEX	06/12/1963	US	0.0%	492	Precious Metals
Corn	EURONEXT	05/09/2003	FR	2.9%	152	Green Seeds
Rapeseed	EURONEXT	10/28/1994	FR	0.5%	255	Green Seeds
Wheat, Milling	EURONEXT	01/04/1999	FR	18.8%	204	Green Seeds
Sugar	CZCE	01/06/2006	CN	1.4%	117	Softs
Corn	DCE	09/01/2004	CN	6.0%	136	Green Seeds
Soybeans No. 1	DCE	01/04/2004	CN	4.8%	144	Green Seeds
Soy Meal	DCE	01/04/2004	CN	9.0%	144	Green Seeds
Pure Terephthalic Acid	CZCE	05/08/2008	CN	7.1%	92	Industrial Material
Cotton No. 1	CZCE	05/09/2005	CN	2.0%	128	Industrial Material
Natural Rubber	SHFE	05/08/2002	CN	0.3%	164	Industrial Material
Aluminum	SHFE	05/08/2002	CN	0.0%	164	Industrial Material

Copper Cathode	SHFE	05/08/2002	CN	0.0%	164	Industrial Material
Steel Rebar	SHFE	03/27/2009	CN	6.9%	77	Industrial Material
Zinc	SHFE	05/23/2007	CN	0.0%	103	Industrial Material
Cocoa #7	LIFFE	06/03/1986	UK	0.1%	355	Softs and Live Cattle
Coffee, Robusta (10 Tonne)	LIFFE	08/01/2008	UK	3.0%	88	Softs and Live Cattle
Sugar #5, White	LIFFE	04/11/1990	UK	0.1%	309	Softs and Live Cattle
Wheat	LIFFE	08/06/1991	UK	14.3%	293	Green Seeds
Gas-Oil-Petroleum	IPE	06/03/1986	UK	0.0%	355	Energy
Natural Gas	IPE	02/03/1997	UK	0.9%	227	Energy
Crude Oil, Brent / Global Spot	IPE	07/24/1989	UK	0.0%	318	Energy
Copper	LME	01/04/1986	UK	0.0%	357	Industrial Materials
Aluminum	LME	01/06/1987	UK	0.0%	341	Industrial Materials
Aluminum Alloy	LME	06/10/1992	UK	0.0%	276	Industrial Materials
Lead	LME	05/01/1987	UK	0.0%	348	Industrial Materials
Nickle	LME	05/01/1987	UK	0.0%	348	Industrial Materials
Tin	LME	01/06/1989	UK	0.0%	319	Industrial Materials
Zinc	LME	04/01/1989	UK	0.0%	324	Industrial Materials
Crude Oil	TOCOM	11/14/2001	JP	0.1%	171	Energy
Gasoline	TOCOM	07/05/1999	JP	0.0%	198	Energy
Azuki Beans	TOCOM	05/06/1993	JP	2.3%	272	Green Seeds
Corn,No. 3	TOCOM	08/16/1994	JP	0.9%	257	Green Seeds
Soybeans, IOM	TOCOM	05/06/1993	JP	1.6%	272	Green Seeds
Rubber #3	TOCOM	12/21/1992	JP	0.0%	280	Industrial Material
Gold	TOCOM	12/21/1992	JP	0.0%	278	Precious Metals

Palladium	TOCOM	12/21/1992	JP	16.1%	276	Precious Metals
Platinum	TOCOM	12/21/1992	JP	0.0%	278	Precious Metals
Coffee, Arabica Type 4/5	BMF	05/22/2006	BR	16.9%	115	Softs and Live Cattle
Corn	BMF	05/22/2006	BR	11.1%	72	Green Seeds
Cattle, Live	BMF	05/22/2006	BR	0.2%	116	Softs and Live Cattle
Barley	NCDEX	12/11/2006	IN	3.9%	109	Green Seeds
Chana	NCDEX	04/19/2004	IN	0.3%	96	Green Seeds
Coriander	NCDEX	08/11/2008	IN	10.1%	88	Green Seeds
Jeera	NCDEX	02/03/2005	IN	0.5%	94	Green Seeds
Soybeans	NCDEX	05/02/2008	IN	0.5%	96	Green Seeds
Soybean Oil	NCDEX	05/02/2008	IN	0.3%	94	Green Seeds
Turmeric	NCDEX	03/02/2009	IN	0.5%	97	Green Seeds
Crude Oil, Oman	DME	06/01/2007	UAE	3.6%	103	Energy
Canola / No. 1	WCE	09/03/1974	CA	4.7%	468	Green Seeds
Palm Oil, Crude	MDEX	01/04/2004	MAS	0.3%	168	Green Seeds
Maize, White	SAFEX	01/01/2004	SF	3.4%	144	Green Seeds
Maize, Yellow	SAFEX	01/01/2004	SF	4.1%	144	Green Seeds
Soya	SAFEX	01/01/2004	SF	12.2%	141	Green Seeds
Sunflower	SAFEX	01/01/2004	SF	6.9%	144	Green Seeds
Wheat	SAFEX	01/01/2004	SF	12.6%	144	Green Seeds
Rubber, RSS3	SGX	01/03/2007	SG	17.3%	105	Industrial Material
Rubber, TSR20	SGX	01/03/2007	SG	0.6%	105	Industrial Material