

Does Policy Uncertainty Affect Mergers and Acquisitions?*

Alice Bonaime

University of Arizona

Huseyin Gulen

Purdue University

Mihai Ion

University of Arizona

First draft: March 2016

This draft: April 2017

Abstract

Political and regulatory uncertainty is strongly negatively associated with merger and acquisition activity at the macro and firm levels. The strongest effects are for uncertainty regarding taxes, government spending, monetary and fiscal policies, and regulation. Consistent with a real options channel, the effect is exacerbated for less reversible deals and for firms whose product demand or stock returns exhibit greater sensitivity to policy uncertainty, but attenuated for deals that cannot be delayed due to competition and for deals that hedge firm-level risk. Contractual mechanisms (deal premiums, termination fees, MAC clauses) unanimously point to policy uncertainty increasing the target's negotiating power.

Keywords: Mergers and acquisitions, Policy uncertainty, Real options

JEL codes: G18, G34

*This paper has benefited from comments and discussions with Leonce Barger, Jon Garfinkel, Andrew Greenland, Kristine Hankins, Jarrad Harford, Yeejin Jang, Brandon Julio, Kathy Kahle, Alyssa Kerr, Sandy Klasa, David Moore, Stefano Rossi, Jessamyn Schaller, Rick Sias, Aazam Virani, Jessie Wang, Jin Xu, Deniz Yavuz and seminar participants at the Arizona State University/University of Arizona Finance Conference and the University of Oregon. We thank Billy Beggs and David Yin for excellent research assistance.

1. Introduction

Mergers and acquisitions (M&As) represent substantial capital reallocations with an estimated aggregate volume of \$1.34 trillion per year. Their sheer magnitude, coupled with their ability to create synergies, renders M&As important to academics, practitioners, and policy makers. Prior literature devotes considerable effort to understanding why M&A activity exhibits substantial variation over time.¹ We contribute to this ongoing discussion by documenting another important source of variation in M&A activity: uncertainty surrounding taxes, government spending, and monetary and regulatory policy—or “policy uncertainty.”

A budding literature asserts that policy uncertainty impacts the global economy.² In the context of M&As, policy uncertainty could be an important source of risk as it could lead to increased uncertainty about target firms’ standalone values or the value of deal synergies. Practitioners and the popular press have publicly speculated about an inverse relation between policy uncertainty and M&A activity. In 2014 Pricewaterhouse Coopers asserted that the “stabilization of the U.S. political and economic environment resulted in improved M&A markets.”³ The popular press agrees: In 2013 *Bloomberg* claimed that the completion of the U.S. Presidential election “set the stage” for larger M&A deals,⁴ and a 2014 article in *Forbes* argued that “factors such as a lack of resolution on the debt ceiling” contributed to weaker than expected M&A activity in the prior year.⁵

We examine the relation between policy uncertainty and M&A activity from 1985 to 2014 using the Baker, Bloom, and Davis (2016) (henceforth, BBD) index to quantify policy uncertainty. The BBD index is a weighted average of (i) the frequency of articles related to policy uncertainty in ten

¹E.g., Previously documented sources of the variation in M&A activity include bidder and target valuations (Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004; Rhodes-Kropf, Robinson, and Viswanathan, 2005; Dong et al., 2006), procyclicality (Maksimovic and Phillips, 2001), industry shocks (Mitchell and Mulherin, 1996; Harford, 2005), product market considerations (Hoberg and Phillips, 2010), risk management (Garfinkel and Hankins, 2011), corporate liquidity (Almeida, Campello, and Hackbarth, 2011), and CEO traits and preferences (Goel and Thakor, 2010; Yim, 2013; Ferris, Jayaraman, and Sabherwal, 2013; Jenter and Lewellen, 2015).

²At the macroeconomic level, policy uncertainty influences capital flows, drives the business cycle, and impedes economic recovery (Bloom et al., 2014; Baker, Bloom, and Davis, 2016; Julio and Yook, 2016). At the firm level, policy uncertainty affects cash holdings (Julio and Yook, 2012), capital expenditures (Gulen and Ion, 2016; Jens, 2016), research and development (Atanassov, Julio, and Leng, 2016), stock prices (Pastor and Veronesi, 2012), and the decision to raise equity (Colak, Durnev, and Qian, 2016).

³<http://www.pwc.com/us/en/deals/publications/assets/pwc-us-technology-deal-insights-2013.pdf>.

⁴“M&A Surges as Confidence Spurs Deals in Computers to Consumer,” *Bloomberg Business*, February 14, 2013.

⁵“6 Reasons 2014 Will Be a Strong Year for M&A Activity,” *Forbes*, January 13, 2014.

leading U.S. newspapers, (ii) tax code change uncertainty, (iii) monetary policy forecast disagreement, and (iv) fiscal policy forecast disagreement. The BBD index significantly correlates with events ex-ante expected to generate policy-related uncertainty and withstands extensive checks, including a detailed human audit.⁶

We begin our empirical analysis at the macroeconomic level by quantifying the effect of policy uncertainty shocks on aggregate M&A deal value and volume. We estimate a Vector Autoregression (VAR) with M&A activity, the BBD policy uncertainty index, and macroeconomic controls including proxies for mispricing, market liquidity, and implied stock-market volatility. Our results suggest that a one standard deviation increase in policy uncertainty is associated with a 6.6% decrease in aggregate M&A deal value and a 3.9% decrease in the number of deals during the next 12 months. Moreover, consistent with deals being “lost” rather than postponed, there is no evidence of a subsequent uptick in M&A activity.

Next, we estimate the effect of policy uncertainty on the firm-level decision to engage in M&A activity. Specifically, we model the likelihood of announcing an acquisition in year t as a function of policy uncertainty as well as macroeconomic and firm-level controls in year $t-1$. The challenge is the possibility that policy uncertainty could simply capture the effect of other macroeconomic forces previously shown to affect M&A activity, leading to an omitted variables bias in our estimates. Therefore, our analysis includes a host of economic indicators that help alleviate this concern. First, we address the concern that poor investment opportunities could drive our results. Specifically, we include four standard proxies for expectations of future economic conditions and control for industry economic shocks and credit conditions as in [Harford \(2005\)](#). Next, we control for the possibility that high policy uncertainty could coincide with depressed valuations by including macro-level and industry-level proxies for valuation waves. Finally, to ensure that our results are driven by *policy*-related uncertainty and not some other aggregate source of uncertainty, we include four proxies for general economic uncertainty in all our specifications.

After controlling for the aforementioned variables, we identify a significant negative relation between policy uncertainty and acquisition likelihood, which implies that the effect of policy un-

⁶Although other policy uncertainty proxies based on election years certainly hold merit, the BBD index also accounts for policy uncertainty unrelated to elections. This feature is beneficial given the high variation in M&A activity in non-election years. Further, the BBD policy uncertainty index should capture not only the effect of elections but also the extent to which election outcomes are uncertain.

certainty on M&A activity is distinct from the effect of more general economic conditions. Our results suggest that a one standard deviation increase in policy uncertainty is associated with an 11.74% decline (i.e., a drop in the unconditional mean likelihood from 14% to 12.35%) in the probability of a firm announcing an acquisition the next year. In addition, we find no evidence that the deals delayed during high policy uncertainty periods get completed at a later time, suggesting that the effect of policy uncertainty on M&A activity is not short-lived. Finally, we show that the dampening effect of policy uncertainty on M&A activity is significant enough to delay merger waves.

To uncover the channels through which policy uncertainty affects merger decisions, we investigate four distinct (but not mutually exclusive) possibilities. First, real options theory predicts that high levels of uncertainty will increase the value of the option to delay investments (e.g., [Bloom, 2009](#)), increasing the incentive to postpone acquisitions. Second, macroeconomic uncertainty could increase the likelihood that the target’s value decreases in the interim period between deal announcement and completion, discouraging merger activity ([Bhagwat, Dam, and Harford, 2016](#)). Third, a more uncertain economic environment could increase merger announcements if managers believe that limited investor attention allows them to more easily engage in empire building without immediate consequences ([Duchin and Schmidt, 2013](#)). Fourth, higher uncertainty could increase the use of mergers as a risk management tool ([Garfinkel and Hankins, 2011](#)). We examine each of these channels and briefly summarize our results below.

We test three predictions related to the real options channel. First, the importance of the option to delay should depend on the extent to which the investment in question can be reversed. Hence, if policy uncertainty operates primarily by affecting the value of the option to delay, then its effect should be stronger for more irreversible deals. Using four different measures of investment irreversibility at the target level, we find that indeed, policy uncertainty has a stronger (more negative) effect on acquisitions of targets that represent more irreversible investments. Second, the option to wait should play a smaller role in acquisitions which are more costly (or impossible) to delay. Consistent with this prediction, we find that policy uncertainty has a stronger effect on deals involving acquirers or targets in industries with high concentration or low merger activity, where competition for the target is presumably lower and deals can be postponed more easily. Third, the extent to which policy uncertainty increases the value of the option to delay should depend

on the sensitivity of the firm’s value to policy shocks. Supporting this prediction, we find that policy uncertainty has a more detrimental impact on merger activity in industries that rely more on government spending and in industries with returns with higher BBD index loadings.

If policy uncertainty affects merger activity primarily by increasing interim risk, we expect its effect to be stronger (more negative) for deals which are ex-ante expected to have longer interim periods (i.e., more time in which the target’s value can decrease). We find that periods of high policy uncertainty are not associated with significantly shorter *observed* interim periods, or a higher prevalence of tender offers or private deals (both of which are *expected* to have significantly shorter interim periods). These results are inconsistent with the idea that policy uncertainty operates through the interim risk channel. We attribute the difference between our results and those of [Bhagwat, Dam, and Harford \(2016\)](#), who show that the negative effect of the VIX on merger activity is restricted to public firms, to the idea that policy uncertainty and the VIX operate over different horizons. We find that the VIX predicts one-month-ahead M&A activity while policy uncertainty predicts one-year-ahead M&A activity. This finding is consistent with the idea that the VIX, a measure of short-term uncertainty (one month, by construction) operates by increasing the value of the seller’s put (a shorter maturity option), while policy uncertainty, a longer-horizon uncertainty measure, operates by increasing the value of the option to delay (a longer maturity option).

To test if policy uncertainty enables empire-building, we start by investigating if high policy uncertainty periods are associated with lower deal quality. We compare bidder announcement returns and long term performance (ROA and sales growth) over periods with above- versus below-median policy uncertainty and find no significant difference in deal quality. Further, we investigate if the negative relation between policy uncertainty and M&A activity is moderated by better corporate governance or by CEOs’ incentives to take on risk. We find no significant interactions between policy uncertainty and proxies for corporate governance and CEO characteristics (delta, vega, and overconfidence). These results cast doubt on the idea that policy uncertainty increases the number of deals motivated by empire-building.

If policy uncertainty encourages managers to use mergers as a risk-management tool, we should observe a positive relation between policy uncertainty and the likelihood of announcing a merger that acts as an operational hedge. Consistent with this prediction, we find that policy uncertainty

increases the likelihood of engaging in vertical mergers and of acquiring a foreign firm (which presumably would reduce exposure to domestic policy risks). While these findings support the notion that operational hedging plays a role in how policy uncertainty affects merger decisions, it is important to note that risk management cannot be the primary mechanism through which policy uncertainty affects M&A activity. If so, we should observe a positive average relation between policy uncertainty and acquisitions, which is the opposite of what we find in the data.

Our cross-sectional tests provide overwhelming support for the hypothesis that policy uncertainty affects merger decisions primarily by increasing the value of the option to wait. This finding has important implications not only for the type of *firms* that engage in merger activity, but also on the type of *deals* that take place. Specifically, if high policy uncertainty encourages firms with the option to delay to wait, then firms making acquisitions when policy uncertainty is high are selected from the population of acquirers for which delaying is more costly. The implication is that targets should be able to negotiate better deals when policy uncertainty is high. Consistent with this prediction, we find that policy uncertainty increases deal premiums, decreases the level and incidence of target termination fees, and increases MAC exclusions (i.e., it becomes more difficult for acquirers to back out of deals). To our knowledge, this study is the first to uncover a connection between uncertainty and the balance of bargaining power in M&A deals.

From a policy-maker's standpoint, it is important to ask if the negative effect of policy uncertainty depends on the type of policy generating the uncertainty. To answer this question, we use the ten category-specific indices of policy uncertainty provided by [Baker, Bloom, and Davis \(2016\)](#). We find that uncertainty related to monetary policy, fiscal policy (taxes and government spending), and regulation (especially financial regulation) has a strong negative effect on M&A activity, while the uncertainty related to health care, entitlement programs, national security, trade policy, and sovereign debt does not meaningfully impact merger decisions. This finding is particularly important for policy-makers because it shows that some sources of policy uncertainty can be significantly more detrimental than others.

An underlying theme that emerges from our analysis is that different sources of uncertainty will affect different firms for different reasons. While convenient to group previous studies in the literature ([Bhagwat, Dam, and Harford, 2016](#); [Duchin and Schmidt, 2013](#); [Garfinkel and Hankins, 2011](#)) as investigations of uncertainty and M&A activity, they are in fact investigating different

components of uncertainty (so much so that they generate opposite predictions). We contribute to this work by focusing on another uncertainty dimension—policy uncertainty. We are careful to investigate whether our results are unique and capture a new relation between M&A activity and uncertainty. In the next section, we expand further on how our paper builds upon these and other prior studies.

2. Related literature and relative contribution

This study contributes to two broad strands of literature. The first explains variations in merger and acquisition activity; the second links policy uncertainty to real economic outcomes.

2.1. Determinants of merger and acquisition activity

It is important to understand which factors contribute to the ebb and flow of M&As because such activities cultivate innovation (Phillips and Zhdanov, 2013; Bena and Li, 2014) and synergies (Betton, Eckbo, and Thorburn, 2008; Sheen, 2014; Devos, Kadapakkam, and Krishnamurthy, 2009; Wang and Xie, 2009). Prior work shows that bidder and target valuations (or misvaluations) affect M&A activity (e.g., Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004; Rhodes-Kropf, Robinson, and Viswanathan, 2005; Dong et al., 2006). Others show that M&A likelihood is related to the business cycle (Maksimovic and Phillips, 2001), product-market considerations (Hoberg and Phillips, 2010), risk management (Garfinkel and Hankins, 2011), corporate liquidity (Almeida, Campello, and Hackbarth, 2011), and CEO traits and preferences (Goel and Thakor, 2010; Yim, 2013; Ferris, Jayaraman, and Sabherwal, 2013; Jenter and Lewellen, 2015). We offer a fresh perspective on variation in M&A activity. While a well-established literature shows that economic and regulatory shocks contribute to merger waves, (e.g., Mitchell and Mulherin, 1996; Harford, 2005), we purport that *uncertainty* surrounding shocks—specifically shocks related to taxes, government spending, and monetary and regulatory policy—deters the start of merger waves and curbs M&A activity at the macro and firm levels.

Extant literature has yet to reach a consensus on the important, but complex question, of how uncertainty impacts merger activity. Using past operating income volatility and the cost of goods sold to proxy for future cash flow uncertainty, Garfinkel and Hankins (2011) find that increases in

cash flow uncertainty lead firms to vertically integrate, commencing merger waves. Their findings are consistent with a risk management motive for mergers, i.e., an increase in uncertainty encourages managers to operationally hedge via vertical integration. [Duchin and Schmidt \(2013\)](#) also find a positive link between uncertainty and merger activity. Specifically, they suggest that merger waves increase firm level uncertainty, thereby spurring mergers motivated by empire-building. Our approach differs from these studies in that we examine more difficult to diversify macroeconomic (as opposed to firm-level) uncertainty and focus on a particular source of aggregate uncertainty: the political and regulatory system. Consistent with vertical mergers reducing risk, we find they are more likely when policy uncertainty is high. However, our results suggest an overall negative relation between policy uncertainty and M&As. Further, policy uncertainty does not appear to interact with corporate governance.

Our paper is closer in spirit to [Bhagwat, Dam, and Harford \(2016\)](#), who show that increases in market-wide implied volatility (the VIX) are associated with weaker M&A activity. The authors show that this inverse relation between the VIX and deal volume is concentrated in (i) public targets, which are subject to longer waiting periods between deal announcement and consummation; (ii) concentrated industries, whose deals would be more subject to anti-trust scrutiny; and (iii) large deals. This evidence suggests that macroeconomic uncertainty affects M&A activity by increasing the risk of deal termination or renegotiation (i.e., interim risk). We build upon this literature establishing a relation between uncertainty and M&A activity by examining *policy* uncertainty and showing that it operates through a distinct channel: real options.

The evidence in [Bhagwat, Dam, and Harford \(2016\)](#) also suggests the VIX does not predict the likelihood of becoming a takeover target at the firm level. Only firm-level volatility and beta have predictive power, and only in large deals. Results are similar at the industry level. We show that firm-level volatility coefficients are consistently negative in acquisition likelihood models, but policy uncertainty coefficients remain negative and statistically significant when we control for firm-level volatility. Hence, we find no evidence that the negative effect of policy-specific uncertainty on M&A activity is absorbed by firm-level volatility.

2.2. Policy uncertainty and economic outcomes

Our paper also contributes to a new and growing literature linking policy uncertainty to real economic outcomes. [Baker, Bloom, and Davis \(2016\)](#) use their index to show that increases in policy uncertainty are associated with upticks in stock price volatility and reductions in industrial production and employment. [Julio and Yook \(2016\)](#) find that election cycles impact foreign direct investment. [Bloom et al. \(2014\)](#) show that policy uncertainty shocks foreshadow substantial drops in GDP, driving business cycles. We are careful to ensure that the negative relation between policy uncertainty and M&A activity continues to hold even after controlling for various forward-looking measures of general macroeconomic conditions.

Another branch of the literature links policy uncertainty to asset prices. [Pastor and Veronesi \(2012\)](#) develop a model linking policy uncertainty and stock prices. Empirical work shows that policy uncertainty commands a risk premium ([Pastor and Veronesi, 2013](#)), forecasts market returns ([Brogaard and Detzel, 2015](#)), contributes to return volatility ([Boutchkova et al., 2011](#)), and is priced in the options market ([Kelly, Pastor, and Veronesi, 2016](#)). [Akey and Lewellen \(2016\)](#) examine the effect of election outcomes on policy sensitive firms and find that policy sensitive firms that donated to candidates who ultimately won the election experience significant reductions in risk (implied volatility and CDS spreads) and improved operating performance (sales growth and ROA) and value (Tobin’s q). In our study, we draw upon their definition of “policy sensitive” firms (those with high stock price sensitivity to the BBD index) to identify cross-sectional variation in exposure to policy uncertainty.

Our paper relates to the literature examining the effects of policy uncertainty in other corporate finance settings including equity issuance and investment policy. Prior literature shows that firms are less likely to raise equity through IPOs ([Colak, Durnev, and Qian, 2016](#)) and SEOs ([Jens, 2016](#)) during gubernatorial election years. In a cross-country study, [Julio and Yook \(2012\)](#) show that firms reduce capital expenditure around election years. For the United States, prior studies document a negative and significant relation between capital expenditures and policy uncertainty using the BBD index ([Gulen and Ion, 2016](#)) and gubernatorial elections ([Jens, 2016](#)). M&As are distinct from capital expenditures and, in contrast, provide the empirical advantage of directly observing the investment in question: the target firm.

Our study establishes an important link between the two aforementioned literatures. The relation between policy uncertainty and M&A activity has been largely ignored in academic studies. Two notable exceptions are contemporaneous working papers by [Cao, Li, and Liu \(2015\)](#) and [Chen, Cihan, and Jens \(2016\)](#). [Cao, Li, and Liu \(2015\)](#) document a significant effect of national elections on cross-border acquisitions; elections at home encourage home-country acquirers to seek targets abroad and deter outside acquirers from targeting home-country companies. Our cross-sectional tests incorporate cross-border acquisitions and corroborate their findings. However, by focusing on US-based acquirers our study holds constant other country-specific factors that could relate to M&A activity. This framework also allows us to perform a rich set of cross-sectional tests employing detailed firm-level accounting and stock price data. [Chen, Cihan, and Jens \(2016\)](#) show that firms shift M&A activity to earlier quarters during gubernatorial election years. Unlike our study, their aim is not to explain whether policy uncertainty affects acquisition likelihood. Instead, in addition to examining the timing of acquisition announcements, they focus on method of payment and deal size, finding that acquisitions conducted during gubernatorial election years are more likely to be financed entirely through stock and, in the case of serial acquisitions, are smaller.

3. Data

In this section, we describe the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index, as well as our merger and acquisitions data. We conclude by outlining our sources for macro-level, industry-level, and firm-level control variables.

3.1. Measuring policy uncertainty

We measure policy-related economic uncertainty using the [Baker, Bloom, and Davis \(2016\)](#) (BBD) index,⁷ which is constructed as a weighted average of four components related to news, tax code changes, and dispersion in forecasts of monetary and fiscal policies. The news component includes policy uncertainty related to all types of policies, as long as these events are covered in the news. Specifically, beginning in 1985 the news component measures policy uncertainty identified through an automated search of ten large newspapers. For each newspaper, the number of articles containing

⁷We thank Scott Baker, Nick Bloom and Steven Davis for making the index and its components available at <http://www.policyuncertainty.com/>.

‘uncertainty’ or ‘uncertain’; ‘economic’ or ‘economy’; and ‘congress’, ‘legislation’, ‘white house’, ‘regulation’, ‘federal reserve’, or ‘deficit’ is counted each month. This count is then scaled by the total number of articles reported in the same newspaper that month, resulting in ten time-series of monthly percentages of news articles related to policy uncertainty. The time-series from each newspaper is normalized to unit standard deviation and these ten normalized series are then summed within each month. The resulting monthly index is then scaled to have a mean of 100 from 1985 to 2009.

The other components capture specific types of policy uncertainty. The second component of the BBD index estimates tax-related uncertainty on an annual basis using data from the Congressional Budget Office. Each year, the tax index is a measure of the discounted value of the revenue effects on all tax provisions set to expire during the subsequent ten years. The last two components of the BBD index capture forecaster disagreement about future monetary and fiscal policies from the Survey of Professional Forecasters provided by the Federal Reserve Board of Philadelphia. Specifically, the third component is the interquartile range of Consumer Price Index (CPI) forecasts, while the fourth is the interquartile range of the forecasts of purchases of goods and services by federal, state, and local governments.

We present summary statistics on the overall index and its components in Table 1. Panel A shows the distribution of these measures during our sample period (from 1985 to 2014). The overall BBD index is calculated by normalizing each of the above components and taking a weighted average as follows: $1/2$ for the news-based component, $1/6$ for the tax component, $1/6$ for CPI forecast disagreement, and $1/6$ for government spending forecast disagreement. The resulting aggregate policy uncertainty index averages 107 during our sample period. Panel B of Table 1 illustrates that the overall index correlates with each of its components in an expected fashion. Further, the components correlate significantly but imperfectly with one another, with correlation coefficients ranging from 0.07 to 0.48. Consistent with the evidence presented by [Baker, Bloom, and Davis \(2016\)](#) that this measure captures policy uncertainty, Figure 1 shows that the BBD index clearly increases around events which are ex-ante expected to increase policy-related uncertainty, such as recessions (shaded areas), financial crises, and wars.

3.2. Mergers and acquisitions data

Our merger and acquisitions data are from Thompson Financial’s Securities Data Company (SDC). Our sample spans from 1985 to 2014 to match the availability of the policy uncertainty index. Following prior literature, we only include deals with a value of at least \$1 million (in 2014 dollars), and for which the acquirer owns less than 50% of the target’s shares before the announcement and obtains 100% of the shares through the deal. Table 2 presents summary statistics (dollar values are reported in 2014 dollars) of the full sample of 151,925 merger and acquisition deals worth a total of \$1.34 trillion per year (on average). The average deal size is \$266 million, but the distribution is skewed: The median deal is only \$28 million.

Publicly traded acquirers based in the U.S. are associated with larger deals. Deals initiated by U.S.-based, public acquirers comprise 27% of all deals reported in SDC but 38% of aggregate deal value. Our firm-level tests restrict our sample to U.S.-based, publicly traded acquirers with available data from CRSP and Compustat, which generates a sample of 32,286 individual merger and acquisition announcements. Of these deals, 83% are acquisitions of domestic targets, valued at \$442 million on average. The remaining 17% are acquisitions of foreign (non-U.S.) targets, valued at \$425 million on average.

In Figure 2, we restrict our attention to deals for which the acquirer is a U.S. public firm, and we plot the monthly total deal value (top panel) and total number of deals (bottom panel) with the monthly BBD policy uncertainty index.⁸ Both plots suggest that periods of high policy uncertainty are generally accompanied by less merger activity. The BBD index has a correlation of -37% with total deal value and -49% with the number of deals, both significant at the 1% level. This negative relation appears pervasive throughout our entire sample and is not restricted to periods of poor economic conditions. For example, in the five-year period following the Great Recession of 2007-2008, policy uncertainty is at all-time highs while merger activity remains depressed, even though general economic conditions improved significantly. Although not a formal test, this figure shows promise that policy uncertainty has independent effects on M&A activity and does not simply proxy for poor economic conditions.

⁸In the interest of readability, all three series are smoothed using a three-month moving average.

3.3. Other variables

We gather a host of data at the firm level, the industry level, and the macroeconomic level to build our control variables. We use Compustat Annual data for accounting variables and CRSP monthly data for stock returns. We use data from the Bureau of Economic Analysis (BEA) Benchmark Input-Output (I-O) Accounts to calculate industry-level sensitivity to government spending and to identify vertical relations between industries in the product market. Our industry competition proxies are from the U.S. Census Bureau and the Hoberg-Phillips Data Library.⁹ We use macroeconomic data are from a variety of sources: interest rate spreads from the St. Louis Federal Reserve; the University of Michigan consumer confidence measure; the Conference Board index predicting GDP growth; the Federal Reserve Bank of Chicago index measuring current economic activity and inflation; the Livingstone Survey measure of GDP growth forecast; Robert Shiller’s adjusted price-earnings ratio; and the Chicago Board Options Exchange’s implied volatility index. To construct our instrument for selection into becoming an acquirer, we use data on mutual fund holdings from Thomson Reuters and data on mutual fund returns from the CRSP Survivorship Bias Free Mutual Fund Database. Appendix A provides a detailed description of all variables used in this study.

4. Policy uncertainty and aggregate M&A activity

We begin our empirical analysis by investigating how the aggregate level of merger and acquisition activity responds to a shock in policy uncertainty by estimating a Vector Autoregression (VAR) with merger activity, policy uncertainty, and controls. We then calculate the Impulse Response Function (IRF) of M&A activity, corresponding to a shock in policy uncertainty. Our VAR uses monthly data and has the following specification:

$$\mathbf{Y}_t = \mathbf{v} + \mathbf{A}_1 \mathbf{Y}_{t-1} + \mathbf{A}_2 \mathbf{Y}_{t-2} + \mathbf{B}_0 \mathbf{X}_t + \mathbf{u}_t \quad (1)$$

where \mathbf{Y}_t is a vector of endogenous variables, \mathbf{X}_t is a vector of exogenous variables and \mathbf{v} , \mathbf{A}_1 , \mathbf{A}_2 and \mathbf{B}_0 are vectors of parameters. Specifically, \mathbf{Y}_t contains the following variables: (1) the natural logarithm of either the monthly aggregate deal value or total number of deals (our two measures of

⁹See <http://hobergphillips.usc.edu>. We thank Professors Gerard Hoberg and Gordon Phillips for making these data available.

aggregate M&A activity), (2) the natural logarithm of the BBD policy uncertainty index, (3) the VXO implied volatility index from the Chicago Board Options Exchange (CBOE) as a measure of general economic uncertainty, (4) the return on the CRSP value-weighted market index to control for general economic conditions, (5) the spread between the Baa rate and the federal funds rate as a measure of market liquidity, and (6) Robert Shiller’s Cyclically Adjusted Price Earnings Ratio (CAPE).¹⁰ As exogenous variables (\mathbf{X}_t) we use (1) the natural logarithm of the aggregate cash holdings obtained from the most recent Compustat annual data to control for the availability of internally-generated funds and (2) a linear time trend variable.¹¹

Because we are interested in how merger activity reacts to a policy uncertainty shock *while holding everything else constant*, we extract shocks in policy uncertainty that are orthogonal to contemporaneous shocks in all the other system variables. To accomplish this, we impose an order on the timing with which an exogenous shock propagates through the variables in our system. In Figure 3, we present the merger-activity IRFs obtained by imposing the following ordering: policy uncertainty, VXO, market return, Baa spread, CAPE, and merger activity.¹²

The estimates presented in Figure 3 show that a policy uncertainty shock has a statistically significant negative effect on both aggregate deal value and the total number of deals, lasting up to 12 months into the future. Cumulating the responses in the first 12 months after a policy uncertainty shock, we find that a 1% increase in uncertainty is associated with an estimated 0.57% decrease in aggregate deal value over the next year, and a 0.34% decrease in the number of deals announced. This effect is economically significant considering that the 75th (90th) percentile of monthly percentage changes in the index is 10% (18%). For example, a one standard deviation increase in uncertainty (from the mean) is associated with an estimated 6.6% decrease in aggregate deal value and a 3.9% decrease in the number of deals announced. Nevertheless, we acknowledge the possibility that these estimates could be contaminated by a series of confounding factors that are difficult to control for in a VAR. (The parameter space would quickly become unmanageable.) We address this concern in great detail in the following section.

¹⁰Please see Appendix A for more details about these variables.

¹¹We treat aggregate cash holdings as exogenous to limit parameter proliferation. However, we verify that our results are qualitatively identical if we treat this variable as endogenous.

¹²Because these orthogonalized IRFs can be sensitive to the ordering imposed, in unreported results we verify that our results are robust to using a wide array of other causal orderings.

5. Policy uncertainty and firm-level acquisition decisions

We model the likelihood of being an acquirer in a given calendar year as a function of the mean level of policy uncertainty in the prior calendar year, controlling for other lagged firm-level and macro-level variables (defined in detail in Appendix A) that could influence M&A likelihood. As described below, we control for four alternative predictors that could be confounding our results: poor investment opportunities, low capital availability, low valuations, and non-policy-related uncertainty. Next, we examine if policy uncertainty generates lost versus postponed deals by examining the long-term relation between policy uncertainty and M&A activity. Finally, we investigate if the negative effect of policy uncertainty on merger activity is strong enough to delay the onset of merger waves.

5.1. Acquisition likelihood

Given the extant evidence that policy uncertainty tends to be countercyclical (e.g., [Bloom et al., 2014](#)), a potential concern is that periods of high policy uncertainty coincide with poor economic conditions or low capital availability, both of which have been shown to affect M&A decisions.¹³ We employ a series of macro-level variables to proxy for expectations about future economic conditions: (i) the University of Michigan index of consumer confidence, (ii) the Conference Board’s proprietary Leading Economic Indicator, (iii) the National Activity Index from the Chicago Federal Reserve Board, and (iv) the average one-year ahead GDP growth forecast from the Livingstone Survey of Professional Forecasters. To avoid multicollinearity issues, we reduce the four macroeconomic proxies for investment opportunities to their first principal component. [Harford \(2005\)](#) finds that capital liquidity significantly affects the relation between economic shocks and M&A activity. Furthermore, he shows that, conditional on sufficient liquidity, industry shocks contribute to merger waves. Hence, following [Harford \(2005\)](#), we construct an industry-level economic shock variable as the first principal component of seven shock variables (profitability, asset turnover, R&D, capital expenditures, employee growth, ROA, and sales growth) for each Fama-French 48 industry. Finally, we control for liquidity using the spread between Baa-rated bonds and the Federal Funds rate as in [Garfinkel and Hankins \(2011\)](#).

¹³To simplify the language, throughout the paper, we use the terms “investment opportunities” and “economic conditions” interchangeably to mean expected profitability of future investment projects.

Both behavioral and neoclassical economic theories lead to predictions that heightened M&A activity could coincide with high equity valuations. If high valuation periods also exhibit low levels of policy uncertainty, failing to control for valuation waves could inflate the effect of policy uncertainty on M&A activity. To address this concern, we proxy for relative valuation using industry-level measures of value and volatility as well as proxies for overall market valuations and investor sentiment. Specifically, we include Shiller’s Cyclically Adjusted Price Earnings (CAPE) ratio, which proxies for relative valuation of the market, with high values indicating overvaluation. Next, following prior literature (e.g., [Harford, 2005](#); [Garfinkel and Hankins, 2011](#)), we calculate industry median Tobin’s q and industry median cumulative returns over the prior three years for each of the [Fama and French \(1997\)](#) 48 industries. High Tobin’s q values and high recent past returns could be indicative of high valuation periods. Finally, market timing could be more likely in industries for which stock prices vary more. Thus, we calculate the industry median standard deviation of monthly returns during the 36-month period ending the prior fiscal year to capture industry return volatility.

It is possible that the BBD policy uncertainty index is correlated with uncertainty generated by other macroeconomic factors, which in turn affects the likelihood of acquisitions. To ensure the effect we are capturing is due to uncertainty related to *policy*, we include four additional proxies for macroeconomic uncertainty. First, we include the [Jurado, Ludvigson, and Ng \(2015\)](#) monthly index of macroeconomic uncertainty which is constructed from the common volatility in the unforecastable component in a system of 279 macroeconomic variables. Next, we include the VXO implied volatility index, released by the Chicago Board Options Exchange. Finally, following [Bloom \(2009\)](#), we augment our model with the cross-sectional standard deviations of monthly returns from CRSP and the cross-sectional standard deviations of year-on-year sales growth from Compustat. To avoid multicollinearity issues, we reduce these four proxies for economic uncertainty to their first principal component.

In [Table 3](#), we use logistic regressions to estimate the likelihood of being an acquirer as a function of the mean level of policy uncertainty in the prior calendar year, controlling for the aforementioned macro-level variables and firm-level controls. Firm controls include log total assets, return on assets (ROA), sales growth, book leverage, cash scaled by total assets, market-to-book ratio, past stock returns, and past stock return volatility. We summarize these controls for the full sample and by

acquirer status in the appendix (see Table A3). Firm-level variables are measured in the fiscal year ending in the previous calendar year; macroeconomic variables are measured (as averages) in the prior calendar year. All our specifications include a time trend variable and industry fixed effects, and standard errors are clustered by firm and year. We show results from our logit models using the overall BBD policy uncertainty index as well as each of its individual components.

The results reported in Table 3 uniformly support the hypothesis that high policy uncertainty is associated with a lower likelihood of being an acquirer the following year. This result is also consistent with the resolution of policy uncertainty being associated with subsequent increases in M&A activity.¹⁴ The marginal effects associated with the policy uncertainty coefficient in the overall-index model (column 1) suggest that a one standard deviation increase in the overall index (from its mean) is associated with a 1.64% decrease in merger likelihood. Given that the unconditional probability of announcing a merger is 14%, a 1.64% decrease is economically meaningful, corresponding to 11.74% of the unconditional probability.¹⁵

The results in Table 3 also reveal that each of the four components of the BBD policy uncertainty index contributes to the negative relation between policy uncertainty and M&A activity. Converting our point estimates to marginal effects, a one standard deviation increase in the news, tax, government spending, and CPI components is associated with a 9.82%, 10.11%, 7.16% and 9.98% decrease in acquisition likelihood, respectively (with respect to the unconditional likelihood).

Finally, to address the possibility that an omitted variable bias remains present in our tests, in the Online Appendix, we propose several plausibly exogenous instruments for policy uncertainty. First, we use the partisan-conflict index of Azzimonti (2016) from the Federal Reserve Bank of Philadelphia, which is based on a frequency count of newspaper articles containing terms related to lawmakers' policy disagreement. Second, similar in spirit to Julio and Yook (2016) we use two variables that measure the political uncertainty generated by gubernatorial elections using data

¹⁴To investigate this interpretation further, in the Online Appendix we examine if deregulation (the resolution of regulatory uncertainty) is associated with upticks in M&A activity. We identify deregulation events as the union of deregulation events from Harford (2005) and Ovtchinnikov (2013) that occur during our sample period. Deregulation events are followed by an increase in merger activity on average, and this effect is stronger in cases where idiosyncratic volatility decreased post-deregulation (i.e., uncertainty was resolved). We also use the BBD regulation and financial regulation indices to identify regulation uncertainty spikes (a increase to at least two standard deviations above the mean then a decrease back below the mean). Regulatory uncertainty spikes differentially affect firms with decreases in idiosyncratic volatility, with mergers becoming more likely if idiosyncratic volatility falls after the regulatory spike. The results suggest that a decline in idiosyncratic volatility is associated with a subsequent increase in M&A activity.

¹⁵In the interest of completeness, additional tests reported in the Online Appendix confirm that this result holds when controlling for each macro-level variable individually.

from the Congressional Quarterly Press Electronic Library. In the first stage, we regress the [Baker, Bloom, and Davis \(2016\)](#) index on each instrument, the macroeconomic controls used in our main specification from Table 3, as well as annual averages of the firm-level controls used in our previous tests. In the second stage, we run the same logistic regressions from Table 3, only this time using the fitted values from the first stage regressions as the policy uncertainty variable.¹⁶ F-statistics from the first stage regressions suggest that all our instruments satisfy the relevance condition. Across all specifications, we find that the negative relation between policy uncertainty and acquisition likelihood remains significantly negative. This result, combined with our extensive set of controls, helps alleviate endogeneity concerns.¹⁷

5.2. *Is the effect of policy uncertainty temporary?*

If high levels of policy uncertainty cause firms to delay, but not forgo, deals, then we expect a reversal in the relation between policy uncertainty and acquisition likelihood over longer time horizons. To investigate this possibility, in Table 4, we use our baseline model to predict acquisition likelihoods up to four years in the future. The first model in Table 4 is identical to our baseline model from Table 3 (column 1), which predicts acquisition likelihood the next year. In subsequent models, we modify the dependent variables to capture acquisition likelihood during the second, third, and fourth years.

If the decline in acquisition likelihood that we originally document is due to firms delaying acquisitions, we should find positive coefficients associated with policy uncertainty when modeling acquisition likelihood past one year in the future. Yet, we observe consistently negative policy uncertainty coefficients up to four years into the future. These are statistically significant when modeling acquisition likelihood at years one and two, but do not differ meaningfully from zero in years three and four. While we do not claim that policy uncertainty causes *all* deals to be lost, the results are consistent with the hypothesis that policy uncertainty results in *enough* forgone deals that a long-term reversal in the policy uncertainty effect is eliminated.

¹⁶We bootstrap our standard errors to account for the fact that we are using generated regressors.

¹⁷We also verify that all our main results from Table 3 hold if we control for presidential, midterm, and gubernatorial elections.

5.3. Merger waves

The literature shows that mergers are clustered in time within industries. While some claim market timing contributes to merger waves (e.g., [Shleifer and Vishny, 2003](#); [Rossi and Volpin, 2004](#); [Rhodes-Kropf, Robinson, and Viswanathan, 2005](#)), a more neoclassical view is that economic shocks drive merger waves (e.g., [Mitchell and Mulherin, 1996](#); [Harford, 2005](#)). The negative association between policy uncertainty and merger announcements documented in [Table 3](#) suggest that another possible determinant of merger waves is the level of policy uncertainty in the economy.

To investigate this possibility, we identify merger waves using the methodology of [Harford \(2005\)](#), adjusted to fit our sample period (i.e., our decades correspond to 1985–1994, 1995–2004, and 2005–2014). In [Table 5](#), we employ industry-level logit models analogous to those in [Table 3](#). However, our dependent variable is now an indicator for the start of a merger wave within an industry, and we replace firm-level control variables with industry averages.

Our results suggest that merger waves are less likely to begin in periods of high policy uncertainty. Converting our coefficients to marginal effects, we estimate that a one standard deviation increase in the overall BBD policy uncertainty index (from its mean) corresponds to a 4.17% decrease in the likelihood of a wave commencing within the average industry. This represents an economically meaningful impact given that the start of merger waves occurs in our sample with 7.53% likelihood. Of the four components of the index, three—news, government spending, and inflation—exhibit statistically significant explanatory power, while there is no evidence the index’s tax component is meaningfully related to merger waves commencement.

6. Why does policy uncertainty affect M&A activity?

In this section we investigate the channels through which policy uncertainty could affect merger decisions. We test predictions related to four different channels. First, higher levels of uncertainty can increase the value of the real option to delay investments (e.g., [Bloom, 2009](#)), increasing the incentive to postpone acquisitions. Second, uncertainty can discourage merger announcements by increasing the likelihood that the value of the target will change in the interim period between announcement and completion (e.g., [Bhagwat, Dam, and Harford, 2016](#)). Third, uncertainty could encourage managers to believe they can engage in empire building without immediate consequences,

increasing the incidence of acquisitions by poorly governed firms (e.g., [Duchin and Schmidt, 2013](#)). Fourth, higher uncertainty could incentivize managers to engage in vertical mergers as a risk-management tool (e.g., [Garfinkel and Hankins, 2011](#)).

6.1. The real options channel

Real options theory suggests that during periods of heightened uncertainty, the value of the option to delay an investment project—in this case an acquisition—increases. In this section, we test three cross-sectional predictions of this theory. Specifically, the negative relation between uncertainty and merger activity should be depend upon (i) the extent to which the investment can be reversed, (ii) the cost of delaying the acquisition, and (iii) the extent to which policy uncertainty translates into firm-level uncertainty (i.e., the firm’s exposure to policy uncertainty).

6.1.1. Investment irreversibility

We use four different proxies for investment irreversibility to test if the negative effect of policy uncertainty on M&A activity is stronger for investments that cannot be easily reversed. One advantage of analyzing merger decisions is that we can observe the investment in question—the target firm. Hence, all our investment irreversibility proxies are measured at the target level.

Our first proxy is target industry capital intensity ratio, measured as the industry-level mean PP&E to total assets ratio. The idea is that firms operating in industries with high capital intensities depend more on illiquid physical assets. We convert this proxy to an indicator variable equal to one if investment irreversibility is high, which in this case, is defined as above the median capital intensity ratio for all industries that year.

Our second investment irreversibility proxy captures target industry-level asset redeployability, as in [Kim and Kung \(2016\)](#). Our data are from the 1997 BEA capital flows table, which contains investments (capital expenditures) for 123 industries across 180 asset categories. We first compute the asset redeployability score for each asset category as the percentage of the industries using it. For each industry, we then calculate the weighted-average of the category-level asset redeployability scores (the weights are given by each asset category’s percentage of total industry capital expenditures). Finally, we construct an indicator variable equal to one if the asset redeployability of the industry is below the median that year (lower redeployability implies higher costs of reversing the

investment).

Following the industrial organization literature (as in [Kessides \(1990\)](#) and [Farinas and Ruano \(2005\)](#)), we construct an industry-level proxy of the extent to which a firm’s costs are sunk. The argument is that sunk costs should be lower (i) for firms renting a larger portion of their physical assets, because renting contracts offer more flexibility than a purchase, (ii) for firms employing capital that depreciates faster, because this type of capital tends to have a shorter life cycle, and (iii) for firms whose assets have an active second-hand market and hence a higher resale value. We thus create the following measures: rent expense, depreciation expense, and PP&E sales over the prior 12 quarters, all scaled by lagged PP&E. Next, we calculate the industry average of each measure. Similar in spirit to [Farinas and Ruano \(2005\)](#) and [Gulen and Ion \(2016\)](#), we characterize an industry as having low sunk costs (i.e., low investment irreversibility) if all three industry proxies are above the median (across all industries) that year.

Our fourth and final proxy for investment irreversibility is motivated by [Shleifer and Vishny \(1992\)](#) and [Almeida and Campello \(2007\)](#), who purport that asset liquidation values are correlated with the cyclicalities of a firm’s sales: Firms operating in highly cyclical industries are unlikely to be able to sell their assets to other firms in the industry during poor economic times, since these other firms are likely negatively affected by the same economic shock. To capture cyclicalities, we classify industries as durables or nondurables at the Fama-French 48 industry level, based on the SIC codes in each industry ([Sharpe \(1994\)](#) finds that durable goods industries are highly cyclical).

Because our investment irreversibility proxies are measured at the target level, we have a potential selection issue. Namely, we only observe target outcomes for announced acquisitions, which may not represent a random sample from the entire population of firms. Thus, we employ a two-stage Heckman model to mitigate this issue. The second stage models the effect of policy uncertainty on the target’s investment irreversibility. The dependent variable in all second stage models equals one in cases of high investment irreversibility. The first stage models the decision to announce an acquisition, similar to the first model in [Table 3](#). For identification purposes, the first stage must include (at least) a covariate that significantly influences the likelihood of becoming an acquirer, but does not affect the type of target selected (i.e., does not belong in the second stage). This variable is meant to instrument for the potentially endogenous selection into the acquirer sample. To find such an instrument, we rely on the findings of [Edmans, Goldstein, and Jiang \(2012\)](#), who

report that mutual funds’ mechanical trades caused by investors’ outflows can affect firm valuation and thus future M&A activity. These findings suggest that a measure of unanticipated fund outflows should satisfy the relevance condition in our Heckman model. On the other hand, we find it unlikely that the acquirer’s unexpected mutual fund flows should significantly influence the *type of target* that the firm is interested in acquiring. Consequently, this variable should also satisfy the exclusion restriction in the context of our study.

To build our instrument, we follow [Edmans, Goldstein, and Jiang \(2012\)](#) and calculate negative price shocks induced by mutual fund flows as opposed to information. The idea is that following extreme outflows mutual funds will sell shares in proportion to current holdings.¹⁸ We include this instrument in the first stage of the Heckman model along with all the control variables used to estimate acquisition likelihoods in our previous tests. The second stage uses all the control variables from the first stage except for the unanticipated mutual fund flows instrument.

The results in Panel A of Table 6 show how investment irreversibility interacts with the relation between policy uncertainty and M&A activity. Consistent with our predictions, across our four different measures of target irreversibility, we find that firms are less likely to acquire targets that represent irreversible investments when policy uncertainty is high. As an example, the industries from the Fama and French 48 classification with highest irreversibility scores across our four proxies are: Steel Works, Rubber and Plastic Products, Fabricated Products, Automobiles and Trucks, Transportation, Restaurants Hotels and Motels, Business Supplies, Mines and Petroleum and Natural Gas. This finding is difficult to reconcile with an alternative explanation in which policy uncertainty simply proxies for some unobserved measure of deteriorating economic conditions. Such an alternative explanation would have the burden of explaining why these confounding economic factors would have a stronger effect on targets with more capital intensity, less redeployable assets, more sunk costs, or operations in durables industries.

6.1.2. *The option to delay and industry competition*

If policy uncertainty affects acquisition likelihood primarily by increasing the value of the option to wait, then this effect should be dampened when delaying the deal is costly. [Grenadier \(2002\)](#)

¹⁸See Appendix A of [Edmans, Goldstein, and Jiang \(2012\)](#) for a detailed explanation of the mutual fund price pressure variable calculation.

provides a theoretical model which shows that the costs of delaying investments can be significantly higher in competitive industries, where the threat of rivals capturing part of the project’s value is higher. Based on the [Grenadier \(2002\)](#) prediction that competition erodes real-option values, we hypothesize that the negative effect of policy uncertainty on merger announcements should be stronger in less competitive (more concentrated) industries where the likelihood of competing bids is lower. We test this prediction both at the target- and acquirer-industry level, using various proxies for competition and the likelihood of competing bids.

We begin with the target industry’s competition in Panel B of Table 6. We structure our tests in the same manner as our investment irreversibility tests from the previous section. That is, we employ two-stage Heckman models in which the first stage models the decision to announce an acquisition and is similar to the first model in Table 3 except that, for identification purposes, we include an additional control variable—the unexpected mutual fund flows instrument described in the previous section. The second stage models the effect of policy uncertainty on concentration or deal volume in the target’s industry. Dependent variables are binary variables equal to one if the target operates in a less competitive industry.

We construct multiple proxies of target-industry competition, beginning with the Herfindahl index. An industry is categorized as highly concentrated (less competitive) if it has an above-median Compustat sales-based Herfindahl index. [Ali, Klasa, and Yeung \(2009\)](#) point out that Compustat competition measures are incomplete because they are based on public-firm data only. They show that concentration measures calculated using U.S. Census Bureau data covering both public and private firms yield results more in line with product market theory predictions. Hence, we also measure target-industry competition using multiple Census-based concentration ratios, defined as the top four, eight, 20, or 50 firms’ output divided by total industry output. We classify an industry as highly concentrated if it has an above-median Census-based sales concentration ratio. While industry concentration measures capture expected competition in the M&A market, merger volume reflects realized competition for similar targets. Thus, our final competition measure is deal volume, defined as the number of targeted firms in the same Fama-French 48 industry scaled by the total number of firms in the industry. We classify industries as having low competition if they fall below the median deal volume the previous year.

Panel B of Table 6 shows that, as policy uncertainty increases, targets are less likely to come from

oligopolistic industries with high concentration or low deal volume. Industry concentration and deal volume should be related to the likelihood of strategic actions from competitors (such as competing bids for the target or its peers), which decrease the value of the option to wait. These results are consistent with the theory of Grenadier (2002) that firms account for the strategic behavior of other competing real option holders—in our case other potential acquirers—when determining optimal option exercise. Hence, these results are consistent with the hypothesis that policy uncertainty decreases merger announcements primarily by increasing the value of the option to delay.

Next, we examine industry competition from the perspective of the acquirer’s industry in Table 7. We test if the effect of policy uncertainty on M&As is weaker if the acquirer operates in a more competitive (less concentrated) industry or if many other firms in the same industry are engaging in acquisitions, thereby reducing a bidder’s ability to delay the deal. Our sample of acquirers consists of publicly traded, U.S. acquirers for which we have more precise industry classifications. Specifically, Hoberg and Phillips (2016) identify a firm’s competitors using product similarity metrics derived from product descriptions in annual 10-K filings. They show that their text-based network industry classifications (TNIC) dominate coarse industry formations based on SIC codes. Hence, we proxy for industry concentration using the sales-based Herfindahl index calculated for Hoberg and Phillips (2016) industries. Because product market competitors are uniquely assigned to individual firms each year, this industry concentration measure has the advantage of being time-varying and firm-specific.¹⁹ Our second competition proxy is acquirer-industry deal volume, which we calculate analogously to target-industry deal volume above.

We structure our tests as logistic models, capturing the likelihood of announcing an acquisition in year t as a function of policy uncertainty, competition, interactions between policy uncertainty and competition, and controls in year $t-1$. We focus on the interaction term coefficients, since they capture the differential effect of policy uncertainty on acquirers with varying delay costs. Results reported in Table 7 suggest that—consistent the predictions of Grenadier (2002)—the relation between policy uncertainty and the likelihood of announcing an acquisition is weaker for firms oper-

¹⁹Our target-level results in Table 6 are robust to replacing the Compustat Herfindahl index with the Hoberg and Phillips (2016) TNIC Herfindahl index. Consistent with the results based on the broader sample, higher policy uncertainty significantly decreases the likelihood of acquiring targets with high (above median) TNIC Herfindahls (the coefficient on the policy uncertainty variable is -0.779 with a t-statistic of -2.42). However, this finding should be interpreted with caution because TNIC industry classifications reduce our sample to only publicly traded U.S. targets after 1995 (a decrease from 21,229 targets to 604 targets).

ating in more competitive industries. Specifically, high policy uncertainty has a significantly more detrimental impact on the likelihood of announcing an acquisition for firms in more concentrated industries and in industries with low deal volume.²⁰ To the extent that deals in oligopolistic industries are less costly to postpone (e.g., fear of a competitors acting strategically is lower), these results are consistent with the explanation that policy uncertainty decreases merger announcements primarily by increasing the value of the option to delay.

6.1.3. *Exposure to policy uncertainty*

If policy uncertainty affects acquisitions through the real options channel, then the strength of this effect should depend on the extent to which policy uncertainty translates into uncertainty about the profitability of the acquirer. To proxy for firm-level exposure to policy uncertainty, we measure (1) how sensitive the firm’s revenues are to government spending and (2) how sensitive the firm’s returns are to the BBD index. We then test if the negative effect of policy uncertainty on M&A activity is stronger for firms with higher exposure to policy uncertainty.

We estimate the percentage of industry sales that can be attributed to government demand using the Benchmark Input-Output (I-O) Accounts table published by the Bureau of Economic Analysis (BEA). Specifically, we estimate x_i/y_i where x_i represents total direct or indirect input necessary from industry i to meet government demand and y_i represents industry i ’s total output. Industry level government spending can be calculated from the industry-by-commodity table in the I-O accounts as follows:

$$x_i = \sum_j a_{i,j} g_j, \quad (2)$$

where $a_{i,j}$ is the value of input from industry i necessary to produce \$1 of industry j ’s output and g_j is the value of output from industry j sold directly to the government at the federal, state, or local level. Since I-O accounts begin in 1982 and are updated every five years, we update our measure accordingly.²¹

²⁰Online Appendix B7 presents acquisition likelihood logits with TNIC Herfindal interactions by BBD index components (Panel A) and subcomponents of the news component (Panel B). The interactive effect of competition with policy uncertainty is strongest for the government spending and news components, and for news subcomponents capturing taxes, government spending, monetary and fiscal policy, regulation (overall and financial), health care and entitlement.

²¹We rely on the BEA concordance tables to merge our measure of dependence on government spending with the rest of our data on three-digit SIC code (prior to 2002) or NAICS codes. If multiple industry codes in the I-O accounts correspond to the same three-digit SIC or NAICS code, we calculate a weighted average of the industry dependencies

We add our proxy for dependence on government spending and an interaction term with policy uncertainty to our baseline logistic regressions. The results, reported in Table 7 show that policy uncertainty continues to be negatively related to the likelihood of announcing an acquisition. Moreover, consistent with the real options channel, the coefficient on the interaction between policy uncertainty and sensitivity to government spending is negative and statistically significant. The results suggest that the effect of policy uncertainty on M&A activity is stronger (more negative) if the firm operates in an industry that is more sensitive to government spending. For example, our proxy indicates that the Defense and Aircraft industries are most reliant on government spending, and this result suggests that high policy uncertainty would more strongly impact M&A activity in these industries.

Next, we examine whether the relation between policy uncertainty and acquisitions varies cross-sectionally with the acquirer’s stock return sensitivity to policy uncertainty, which should capture the firm’s overall exposure to policy risks. Similar in spirit to [Akey and Lewellen \(2016\)](#), we regress each Fama-French 48 industry’s value-weighted monthly excess stock returns on the BBD policy uncertainty index over the 60 months prior to the beginning of the firm’s fiscal year in which we measure acquisition announcements. We supplement our asset pricing model with factors from the Fama-French three-factor model as such:

$$R_{i,t} - R_{f,t} = a_i + p_i BBD_t + b_i(R_{M,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + e_{i,t}, \quad (3)$$

where $R_{i,t}$ is the value-weighted return on industry i in month t , $R_{f,t}$ is the risk-free rate (1-month U.S. T-bill rate), BBD_t is the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index, $R_{M,t}$ is the return on the market (value-weighted portfolio of NYSE, Amex, and NASDAQ stocks), and SMB_t and HML_t are the returns on the size and value factors of [Fama and French \(1993\)](#).

To measure a firm’s return sensitivity to policy uncertainty, we use its industry’s beta coefficient associated with policy uncertainty (p_i). In the last column in Table 7, we add this measure to our baseline specification and interact it with policy uncertainty. We continue to observe a negative relation between policy uncertainty and the likelihood of announcing an acquisition, and this relation is stronger for firms with greater stock price sensitivity to policy uncertainty. For example, we

on government spending, with the weights being a function of total industry outputs.

find that stock returns in the Retail and Defense industries have the highest sensitivity to policy uncertainty. Thus, our tests predict that firms with mergers and acquisitions in these industries will be more sensitive to policy uncertainty. Overall, the cross-sectional results in Table 7 find strong support for the hypothesis that policy uncertainty affects M&A activity through a real options channel.

6.2. *The interim risk channel*

Bhagwat, Dam, and Harford (2016) propose that macroeconomic uncertainty discourages merger announcements because it increases the likelihood that the target’s value will change in the interim period between announcement and completion (i.e., interim risk). Consistent with this view, the authors show that the effect of the VIX on merger activity is strongest for public deals, which are on average subject to a longer interim period.

In Table 8 we test if policy uncertainty operates primarily through the interim risk channel. We split our sample into “high” (above-median) and “low” (below-median) policy uncertainty periods and compare variables correlated with actual and expected interim risk. If policy uncertainty has a stronger negative effect on deals with longer interim periods, then the average interim period of deals announced in high-policy-uncertainty times should be longer than that of deals announced in low-policy-uncertainty times. However, the first row in Table 8 shows no significant difference in observed interim periods across high and low policy uncertainty periods.

Following the same logic, we next study expected interim periods. Interim periods of tender offers are typically less than half as long as interim periods of mergers (Offenberg and Pirinsky, 2015), and acquisitions of private targets are generally completed faster than public targets. Hence, if policy uncertainty operates primarily through the interim risk channel, then high policy uncertainty times should be associated with relatively more tender offers and more private deals. Yet, as shown in the second row of Table 8, the average number of tender offers per year drops from 126 deals if policy uncertainty is low, to only 88 deals if policy uncertainty is high. In addition, the third row of Table 8 shows the percentage of deals involving public targets is almost identical in low and high policy uncertainty periods (12.17% and 12.23%, respectively). As final check, in the Online Appendix we model the likelihood of acquiring a private target using the same controls as in our baseline specification. Each of the four subcomponents of the BBD index (news, tax, govern-

ment spending and CPI) continue to have a significant negative effect on private-target acquisition likelihood. Taken together, these tests reveal no evidence that an increase in expected firm-level interim risk drives the relation between policy uncertainty and M&A activity.²²

It is important to note that, because we investigate a different source of uncertainty, our results do not contradict the findings of [Bhagwat, Dam, and Harford \(2016\)](#). Rather, we hypothesize that the difference in horizon between the two measures of uncertainty (VIX and policy uncertainty) could explain why they affect merger activity in different ways. The results in [Bhagwat, Dam, and Harford \(2016\)](#) are consistent with market-wide volatility increasing the value of the “seller’s put,” i.e., the target’s option to sell itself to the acquirer at the bid price, even if the target’s true value declines during the interim period. The seller’s put and the option to delay differ with respect to their time to maturity. While the average interim period in our sample is 80 days, the option to delay is not restricted to such short horizons, essentially expiring only if and when the target is no longer for sale.

To test the difference in time horizons between these two mechanisms, in [Table 9](#) we follow an analogous approach to [Bhagwat, Dam, and Harford \(2016\)](#) and model the percentage change in aggregate deal volume from one month to the next as a function of the lagged monthly percentage changes in the VIX index and other macroeconomic controls (Shiller’s PE, market returns, rate spread, and cash). Columns 1 through 4 confirm their findings: Increases in the VIX are associated with decreases in deal volume the next month, but the effect is confined to M&As involving publicly traded targets. In subsequent models, we add monthly percentage changes in the BBD policy uncertainty index, first individually (columns 5 through 8), and then controlling for the VIX (columns 9 through 12). The relation between policy uncertainty and M&A activity is insignificant over such a short time period, but the inverse relation between the VIX and deal volume remains significant for public targets.

In Panel B of [Table 9](#), we extend our horizon from monthly percentage changes to yearly (i.e., we predict merger activity over the following year). The difference in horizon greatly influences our findings. The VIX is not meaningfully related to one year ahead deal volume, while increases

²²For completeness, we also verify that policy uncertainty has a significant negative effect on merger activity involving private acquirers. We obtain accounting data and merger announcements for private acquirers from Capital IQ and use a specification that contains all the controls from our baseline model except for the variables requiring stock prices. We identify a policy uncertainty coefficient of -0.358 with a t-statistic of -2.5 , consistent with a negative relation between policy uncertainty and private-bidder acquisitions.

in policy uncertainty are associated with statistically significant decreases in deal volume. This relation holds across all types of targets (public, private, and subsidiaries) and remains strong even after controlling for the VIX. The fact that the VIX predicts one month ahead M&A activity while policy uncertainty predicts one year ahead M&A activity is consistent with the idea that the VIX, a measure of short-term uncertainty (one month, by construction) operates by increasing the value of the seller’s put (a shorter maturity option), while policy uncertainty, a longer-horizon uncertainty measure, operates by increasing the value of the option to delay (a longer maturity option).

6.3. *The empire-building channel*

[Duchin and Schmidt \(2013\)](#) suggest that, due to limited attention, merger waves can increase firm-level valuation uncertainty, making it easier for managers of poorly governed firms to engage in value-destroying deals. Consistent with this hypothesis, the authors demonstrate that firm-level measures of uncertainty increase during merger waves and that the mergers announced during waves have worse long-run performance and corporate governance. The [Duchin and Schmidt \(2013\)](#) results raise the possibility that high policy uncertainty could incite managers of poorly governed firms, who believe this uncertainty allows them to engage in empire-building without immediate consequences, to initiate sub-optimal mergers. It is important to note that this corporate governance mechanism cannot be the *primary* channel through which policy uncertainty affects M&A activity, which implies a positive relation between mergers and policy uncertainty whereas we identify a negative relation in the data. Nevertheless, empire building could still play a role (albeit not dominant) in the way policy uncertainty relates to merger decisions. We investigate this possibility below.

If policy uncertainty significantly increases the number of deals motivated by empire-building, we expect high policy uncertainty periods to be associated with lower quality deals. In [Table 10](#) we present averages of proxies for value-creation, operating performance, and sales growth for periods of low versus high policy uncertainty. We split the sample along the median policy uncertainty value throughout our time period. We then calculate three and five day cumulative abnormal returns (CARs) around acquisition announcements as the buy and hold return on the bidder’s stock net the buy and hold return on the value-weighted CRSP index. The results reveal no evidence of a meaningful difference between announcement CARs for periods of high and low policy uncertainty.

It is possible that the market fails to immediately recognize and impound the acquisition’s

value into prices at the time of the announcements. To address this concern, we turn to longer term measures of operating performance and sales growth. We calculate the change in industry-adjusted return on assets (ROA) from the year prior to the acquisition announcement to the year after. Sales growth is the percentage change in sales from one year to the next. We calculate the change in sales growth as the industry-adjusted sales growth from the year before the acquisition announcement to the year after. Similar to CARs, we find that deals announced in high versus low policy uncertainty periods do not differ meaningfully with respect to these ROA and sales-growth based performance measures. Overall, our results suggest that deals occurring in high policy uncertainty periods are not met with significantly different market reactions, and do not result in different firm performance than the deals announced during low policy uncertainty times. Hence, our findings are inconsistent with the idea that policy uncertainty significantly increases the number of deals motivated by empire-building.

If policy uncertainty encourages managers to engage in empire-building, this effect should be moderated by better corporate governance. Hence, the effect of policy uncertainty on M&A activity should be significantly stronger (more negative) for well governed firms where the empire-building channel is presumably cut off. To test this prediction, in Table 11 we add (one-by-one) the following common corporate governance proxies to our baseline specification, (as well as interaction terms between each proxy and the BBD policy uncertainty index): (1) total ownership of top five institutional investors, (2) the number of blockholders with more than 10% ownership, (3) the number of analysts following the firm, (4) the percent of independent directors, (5) the Bebchuk, Cohen and Ferrell (2009) Entrenchment Index, and (6) CEO pay slice. To ease interpretation, proxies (1), (4) and (6) are converted to decile rankings (taking values 0 through 9). Decile rankings makes the lowest value for each of the six proxies equal to zero, which means the coefficient on the standalone policy uncertainty variable captures the effect of policy uncertainty on acquisition likelihood for firms with the poorest level of corporate governance. The coefficient on the interaction examines the effect of policy uncertainty on acquisition likelihood as governance improves. The results presented in the first six columns of Table 11 show that these interactions are not statistically significant, which indicates that the effect of policy uncertainty on merger activity does not depend on acquirers' corporate governance quality (i.e., their *ability* to engage in empire-building).

Finally, we investigate how policy uncertainty relates to managers incentive and willingness

to engage in empire-building, by interacting the BBD index with CEO vega, CEO delta, and CEO overconfidence (the value of unexercised in-the-money options). If policy uncertainty enables empire-building, then its effect on merger activity should be weaker (less negative) when managers have more incentive to take on risk (higher vega), when their incentives are less aligned with shareholders' (lower delta) and when they are more overconfident. The results, reported in the last three columns of Table 11 show that the interactions between our three proxies and the BBD index are all statistically insignificant. This finding suggests that the effect of policy uncertainty on merger activity is not meaningfully related to managers' incentive or willingness to engage in empire-building. Overall, the tests described in this section show no evidence that policy uncertainty affects M&A activity through an empire-building channel.

6.4. *The risk-management channel*

Garfinkel and Hankins (2011) find that firms that experience an increase in cash-flow volatility are more likely to engage in vertical mergers. The authors posit that this results from managers employing vertical mergers as a risk management tool (i.e., operational hedging) when uncertainty increases. To test if hedging motives could play a role in the relation between policy uncertainty and M&A activity, we investigate if policy uncertainty increases the likelihood of engaging in mergers that reduce exposure to policy uncertainty risk, namely, cross-border or vertical mergers.

If policy uncertainty increases the incentive to engage in risk-management driven deals, then increases in domestic policy uncertainty could prompt U.S. firms to look abroad for acquisition prospects. The intuition is that firms are at risk of experiencing a policy-related shock to their business environment during times of heightened policy uncertainty. One way to partially hedge against such a shock is to acquire a firm less affected by the policy in question. Domestic targets are more likely to be exposed to the same policy shocks as domestic acquirers while foreign firms are less likely to be affected by U.S. policy. Hence, all else being equal, high levels of policy uncertainty should make domestic targets relatively less attractive than foreign targets to U.S. acquirers.

To test this hypothesis, we again face a potential selection issue. That is, we only observe targets for announced acquisitions. Thus, we employ a two-stage Heckman model where the first stage, which models the decision to announce an acquisition, is identical to the first model in Table 3. To meet the Heckman procedure exclusion restriction, we include in the first stage the

unanticipated mutual fund flows instrument described in Section 6.1.1. The second stage predicts the likelihood of acquiring a domestic target, and is presented in the first column of Table 12. Our results show that the likelihood of acquiring domestically versus abroad decreases as policy uncertainty increases. This finding is consistent with acquiring firms preferring to reduce their exposure to domestic policy risks by looking abroad for acquisitions.

Vertical mergers represent an interesting subset of deals because they provide risk management benefits by reducing uncertainty surrounding input or output prices (Garfinkel and Hankins, 2011). Hence, during times of heightened policy uncertainty, *vertical* mergers could actually become *more* attractive for two reasons. First, acquiring a buyer or supplier through a vertical merger could diversify a firm’s exposure to policy risk. Second, firms facing increasing political uncertainty may wish to reduce other types of uncertainty, such as price uncertainty.

We identify vertical mergers using the Benchmark Input-Output (I-O) tables published by the Bureau of Economic Analysis (BEA). Using the Make and Use tables, we estimate the output from industry i required to produce one dollar of output for industry j and vice versa. Following prior literature (e.g., Fan and Goyal, 2006; Garfinkel and Hankins, 2011; Ahern and Harford, 2014), if either value exceeds 1%, we classify the merger as “vertical.”²³

Because we only observe whether or not a merger is vertical if a merger occurs, we employ a two-stage Heckman approach similar to the procedure described above, except that now the second stage models the likelihood of a vertical merger. Our results, presented in the second column of Table 12, imply that the likelihood of vertical mergers increases as policy uncertainty increases. These findings are consistent with firms seeking to reduce firm-level uncertainty during times of high policy uncertainty through vertical integration. Hence, the results in this section suggest that operational hedging plays a role in how policy uncertainty affects certain types of merger decisions. Nevertheless, it is important to recognize that this risk-management channel cannot be the primary mechanism through which policy uncertainty affects M&A activity because this would imply a positive relation between the two, which is not supported by the data.

²³Because I-O accounts are published every five years, we classify vertical industry pairs using the I-O tables published closest in time to the sample year. For example, we match observations from 1985 through 1989 with I-O tables from 1987, observations from 1990 through 1994 with I-O tables from 1992, etc. Because the last I-O table was published in 2007, we match the 2007 table with observations spanning from 2005 to 2014.

7. Which policies matter most?

The results in the previous section strongly support the hypothesis that policy uncertainty affects M&A activity primarily by increasing the value of the real option to delay acquisitions. While previous studies have proposed different channels through which uncertainty may relate to merger decisions (Bhagwat, Dam, and Harford, 2016; Duchin and Schmidt, 2013; Garfinkel and Hankins, 2011), it is important to note that our results do not contradict the findings of these earlier studies. Rather, they point to the idea that different types of uncertainty could affect firms in different ways. In this section, we further investigate this possibility by analyzing if the negative impact of policy uncertainty on M&A activity depends on the type of policy generating the uncertainty.

Baker, Bloom, and Davis (2016) construct category-specific indices of policy uncertainty related to fiscal policy, taxes, government spending, monetary policy, regulation, financial regulation, health care, entitlement programs, national security, trade policy, and sovereign debt. To obtain these measures, the authors count newspaper articles that contain search terms related to the specific type of policy in question in addition to the original search terms for the overall policy-uncertainty index. For example, to measure policy uncertainty related to taxes, the authors count the number of newspaper articles that contain not only the original keywords related to policy, uncertainty and economics (see Section 3.1), but also one or more of the following keywords: “taxes,” “tax,” “taxation,” and “taxed.”²⁴

In Table 13 we report logistic regressions of acquisition likelihood on policy uncertainty and controls. These tests are analogous to our baseline specifications from Table 3. Different from Table 3, however, each column uses a different category-specific policy-uncertainty index. The first four columns reveal that the uncertainty related to fiscal policy (both taxes and government spending) and monetary policy are meaningfully negatively related to future M&A activity. These results confirm the findings from the last three columns of Table 3 in which monetary and fiscal policy uncertainty are measured using forecaster disagreement and future changes in the tax code. Columns 5 and 6 in Table 13 show that uncertainty related to regulation, and financial regulation in particular, also have a strong negative effect on merger activity. This finding is intuitive since

²⁴A full list of the search terms employed to identify each of the category-specific policy uncertainty measures can be found at http://www.policyuncertainty.com/categorical_epu.html.

the regulation uncertainty index is based, in part, on keywords related to M&A (e.g., antitrust, competition policy, merger policy, monopoly, etc.) and the financial sector plays an important role in the execution of M&As.²⁵

The last five columns of the Table 13 reveal that health care, entitlement programs, national security, trade policy, and sovereign debt uncertainty are not meaningfully related to subsequent M&A activity. This results can stem from several factors. First, as we discussed in greater detail in Section 6, the effect of policy uncertainty on acquisitions depends on firms' exposure to the policies driving the uncertainty. If a relatively small number of firms are affected by the above policies, then a meaningful relation between that type of policy uncertainty and aggregate M&A activity is unlikely. For instance, if only a small number of firms are impacted by sovereign debt policies, we are unlikely to find a meaningful relation between sovereign debt uncertainty and aggregate M&A activity. Second, these policies may not generate a high enough level of uncertainty to deter merger activity. To further investigate this issue, we report in the last row of Table 13 the percentage of newspapers articles mentioning policy uncertainty that also mention the keywords pertaining to the specific type of policy reported in each column. These results reveal that sovereign debt, trade policy, and entitlement programs are relatively less common sources of policy uncertainty which can help explain the lack of a strong relation between these types of policy uncertainty and future M&A activity. In contrast, although financial regulation is a less common source of policy uncertainty, it is likely to affect a larger fraction of firms. National security and health care likely are the opposite case—they are often cited as a source of uncertainty (on par with regulation and monetary policy), but could affect a narrower subset of firms.

To summarize, our results reveal that the relation between uncertainty and M&A activity is complex—not all sources of macroeconomic uncertainty affect merger activity in the same manner. While the level of uncertainty is clearly important, both the type of uncertainty and the breadth of firms impacted by the uncertainty are also of importance. This finding has important implications for policy makers because it shows that their indecision with respect to some specific policies

²⁵To provide additional evidence of the relation between policy uncertainty and merger activity, we conduct a LexisNexis search for merger-related policy uncertainty news. Our search terms include the BBD policy uncertainty search terms plus the terms merger or acquisition. To summarize, the relevant articles generally fall into one of three categories: (i) companies weighing political risks before investing abroad, (ii) legal and regulatory uncertainty in highly regulated industries (telecom, utilities, and financial firms) stifling merger activity, and (iii) aggregate deal volume lagging amid uncertainty surrounding the tax code or government spending.

(monetary policy, fiscal policy, financial regulation) can be particularly detrimental to the efficient allocation of capital in the economy.

8. Policy uncertainty and deal characteristics

Our prior analysis reveals that the effect of policy uncertainty on merger decisions is not uniform in the cross-section. Policy uncertainty impacts not only acquisition likelihood but also *which type of firms* engage in M&A activity. In this section we investigate a different dimension of heterogeneity by examining if policy affects the *characteristics of announced deals*. In particular, we are interested in deal characteristics related to the relative negotiating power between targets and bidders: deal premiums, termination fees, and MAC exclusions. Our motivation stems from an implication of our finding that policy uncertainty operates primarily through the real options channel: When faced with high policy uncertainty, potential acquirers who can delay their acquisition, do so. This finding implies that, in times of high policy uncertainty, bidders are selected from the population of firms for which delaying is relatively more costly. Anticipating this, target firms should be able to negotiate better deal terms when policy uncertainty is high.

To investigate this prediction, in Table 14 we model the relation between policy uncertainty and deal characteristics using two-stage Heckman models and present coefficients associated with policy uncertainty for second-stage models. The first stage predicts acquisition likelihood as described in Section 6.1.1. Consistent with our prior analysis, the unit of observation is acquirer-year. The vast majority of acquirers only announce one acquisition per year. However, if a firm announces more than one deal, we average the deal characteristics for the year.

First, we calculate the deal premium as the deal value scaled by the target’s market capitalization four weeks prior to the announcement. We adjust the target market capitalization for the fraction of the firm sought by the bidder. Column 1 in Table 14 shows that acquirers pay significantly higher premiums for targets as policy uncertainty increases. This finding is consistent with the relative negotiating power of the target increasing when policy uncertainty is high.

Second, we examine target terminations fees. It could be that in uncertain times, targets negotiate higher premiums in exchange for a more expensive exit option. Yet, Officer (2003) and Bates and Lemmon (2003) show a positive link between termination fees and deal premiums, likely

because deals with more expensive exit strategies are more likely to be completed. In the second and third columns of Table 14, we find that policy uncertainty is negatively associated with the amount of and likelihood of having a target termination fee, again consistent with increased negotiating power on the part of the target.

Finally, we examine MAC exclusions. MACs serve as free abandonment options for the acquirer if a material adverse event occurs prior to deal completion. MAC exclusions therefore void the acquirer’s abandonment option under specified circumstances, and contracts with more MAC exclusions are associated with a greater likelihood of deal completion (Denis and Macias, 2013). Using a reduced sample of deals for which we know the number of MAC exclusions,²⁶ we find that the number of MAC exclusions increases with policy uncertainty, consistent with acquirers having fewer scenarios under which they can back out of the deal. Overall, the results in this section strongly support the hypothesis that high policy uncertainty increases target firms negotiation power, which is consistent with our view that policy uncertainty operates primarily through a real options channel.²⁷

9. Conclusion

Mergers and acquisitions play an integral role in the allocation of capital. But frictions such as transaction costs, information asymmetry, and managerial behavioral biases can contribute to inefficiencies and lead to suboptimal capital allocation. We study how another potential friction—uncertainty surrounding government policies—could affect M&A activity. Policy uncertainty significantly influences the environment in which firms conduct business, and shocks to policy uncertainty could induce managers to alter their firm’s course of action. Drawing on a new metric developed by Baker, Bloom, and Davis (2016), we study the effect of the policy uncertainty on M&A activity.

We present robust evidence that policy uncertainty negatively influences M&A activity both in the aggregate and at the firm level. The economic magnitude of the effect is significant. A one

²⁶We are very grateful to David Denis and Antonio Macias for sharing their MAC exclusion data.

²⁷Prior policy uncertainty literature (e.g., Julio and Yook, 2012) finds that firms tend to increase cash holdings when policy uncertainty increases. Thus, we examine the relation between policy uncertainty and merger payment method (cash or stock) in the Online Appendix. The results suggest that higher policy uncertainty is associated with an increased likelihood of stock financing for firms that are least likely to be overvalued consistent with the idea that firms hoard cash during uncertain times (as in Julio and Yook (2012)), but are less able to do so if they are overvalued.

standard deviation increase in policy uncertainty is associated with a 6.6% decrease in aggregate M&A deal value, a 3.9% decrease in the number of deals, and a 4.17% reduction in the likelihood of a wave commencing over the next year. At the firm level, a one standard deviation increase in the overall index (from its mean) is associated with a 1.1 percentage point decrease in merger likelihood, or 8.9% of the unconditional probability of announcing a merger. Moreover, we do not observe mean reversion suggesting that these acquisitions tend to be “lost” rather than simply delayed.

We examine four potential channels through which policy uncertainty could impact M&A activity: real options, interim risk, empire-building, and risk management. Cross-sectional evidence strongly supports the real options channel. The effect of policy uncertainty on M&As is stronger for deals involving more irreversible investments and for deals where the acquirer is more sensitive to policy uncertainty, but weaker for deals that cannot be easily delayed. One implication is that firms conducting acquisitions when policy uncertainty is high are those for which delaying is prohibitively costly. Consistent with this prediction, we find that target firms exploit this setting by negotiating better deal terms when policy uncertainty is high.

We also find some evidence consistent with risk management: When policy uncertainty is high, firms are more likely to engage in cross-border or vertical mergers, which could diversify policy or price risk. Nonetheless, our findings suggest that policy uncertainty—unlike other types of uncertainty—does not operate through the interim risk or empire-building channels.

Finally, we show that the *type* of policy uncertainty matters. Uncertainty related to monetary policy, fiscal policy (taxes and government spending), and regulation (especially financial regulation) have the strongest negative effect on acquisition likelihood, while the uncertainty related to health care, entitlement programs, national security, trade policy and sovereign debt does not meaningfully impact M&A activity. From a policy-maker’s standpoint, this finding is particularly important because it shows that some sources of policy uncertainty are more detrimental than others.

References

- Ahern, K.R., Harford, J., 2014. The importance of industry links in merger waves. *Journal of Finance* 69, 527–576.
- Akey, P., Lewellen, S., 2017. Policy uncertainty, political capital, and firm risk-taking. Unpublished working Paper. University of Toronto and London Business School.
- Ali, A., Klasa, S., Yeung, E., 2009. The limitations of industry concentration measures constructed with Compustat data: Implications for finance research. *Review of Financial Studies* 22, 3839–3871.
- Almeida, H., Campello, M., 2007. Financial constraints, asset tangibility, and corporate investment. *Review of Financial Studies* 20, 1429–1460.
- Almeida, H., Campello, M., Hackbarth, D., 2011. Liquidity mergers. *Journal of Financial Economics* 102, 526–558.
- Atanassov, J., Julio, B., Leng, T., 2016. The bright side of political uncertainty: The case of R&D. Unpublished working paper. University of Nebraska, University of Oregon, and Sun Yat-sen University.
- Azzimonti, M., 2016. Partisan conflict, news, and investors expectations. Unpublished working paper. Stony Brook University.
- Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. *Quarterly Journal of Economics*, forthcoming.
- Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. *Journal of Economic Perspectives* 21, 129–152.
- Bates, T., Lemmon, M., 2003. Breaking up is hard to do? An analysis of termination fee provisions and merger outcomes. *Journal of Financial Economics* 69, 469–504.
- Belo, F., Gala, V.D., Li, J., 2013. Government spending, political cycles, and the cross section of stock returns. *Journal of Financial Economics* 107, 305–324.
- Bena, J., Li, K., 2014. Corporate innovations and mergers and acquisitions. *Journal of Finance* 69, 1923–1960.
- Betton, S., Eckbo, E., Thorburn, K., 2008. Corporate takeovers. *Handbook of Corporate Finance: Empirical Corporate Finance* 2, 291–430.
- Bhagwat, V., Dam, R., Harford, J., 2016. The real effects of uncertainty on merger activity. *Review of Financial Studies*, forthcoming.
- Bloom, N., 2009. The impact of uncertainty shocks. *Econometrica* 77, 623–685.
- Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., Terry, S.J., 2014. Really uncertain business cycles. No. w18245, National Bureau of Economic Research.
- Boutchkova, M., Doshi, H., Durnev, A., Molchanov, A., 2011. Precarious politics and return volatil-

ity. *Review of Financial Studies* 25, 1111–1154.

Brogaard, J., Detzel, A., 2015. The asset pricing implication of government economic policy uncertainty. *Management Science* 61, 3–18.

Cao, C., Li, X., Liu, G., 2015. Political uncertainty and cross-border mergers and acquisitions. Unpublished working paper. Southwestern University of Finance and Economics, Cheung Kong Graduate School of Business, and University of Hong Kong.

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

Chen, Z., Cihan, M., Jens, C., 2016. Political uncertainty and firm investment: Project-level evidence from M&A activity. Unpublished working paper. Tulane University and University of Connecticut.

Colak, G., Durnev, A., Qian, Y., 2016. Political uncertainty and IPO activity: Evidence from U.S. gubernatorial elections. *Journal of Financial and Quantitative Analysis*, forthcoming.

Denis, D., Macias, A., 2013. Material adverse change clauses and acquisition dynamics. *Journal of Financial and Quantitative Analysis* 48, 819–847.

Devos, E., Kadapakkam, P., Krishnamurthy, S., 2009. How do mergers create value? A comparison of taxes, market power, and efficiency improvements as explanations for synergies. *Review of Financial Studies* 22, 1179–1211.

Dong, M., Hirshleifer, D., Richardson, S., Teoh, S.H., 2006. Does investor misvaluation drive the takeover market? *Journal of Finance* 61, 725–762.

Duchin, R., Schmidt, B., 2013. Riding the merger wave: Uncertainty, reduced monitoring, and bad acquisitions. *Journal of Financial Economics* 107, 69–88.

Edmans, A., Goldstein, I., Jiang, W., 2012. The real effect of financial markets: The impact of prices of takeovers. *Journal of Finance* 67, 933–971.

Erel, I., Liao, R.C., Weisbach, M.S., 2012. Determinants of cross-border mergers and acquisitions. *Journal of Finance* 67, 1045–1082.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3–56.

Fama, E.F., French, K.R., 1997. Industry costs of equity. *Journal of Financial Economics* 43, 153–193.

Fan, J.P.H., Goyal, V.K., 2006. On the patterns and wealth effects of vertical mergers. *The Journal of Business* 79, 877–902.

Farinas, J.C., Ruano, S., 2005. Firm productivity, heterogeneity, sunk costs and market selection. *International Journal of Industrial Organization* 23, 505–534.

Ferreira, M.A., Massa, M., Matos, P., 2009. Shareholders at the gate? Institutional investors and cross-border mergers and acquisitions. *Review of Financial Studies* 23, 601–644.

- Ferris, S.P., Jayaraman, N., Sabherwal, S., 2013. CEO overconfidence and international merger and acquisition activity. *Journal of Financial and Quantitative Analysis* 48, 137–164.
- Garfinkel, J.A., Hankins, K.W., 2011. The role of risk management in mergers and merger waves. *Journal of Financial Economics* 101, 515–532.
- Goel, A.M., Thakor, A.V., 2010. Do envious CEOs cause merger waves? *Review of Financial Studies* 23, 487–517.
- Grenadier, S.R., 2002. Option exercise games: An application to the equilibrium investment strategies of firms. *Review of Financial Studies* 15, 691–721.
- Gulen, H., Ion, M., 2016. Policy uncertainty and corporate investment. *Review of Financial Studies* 29, 523–564.
- Harford, J., 2005. What drives merger waves? *Journal of Financial Economics* 77, 529–560.
- Hoberg, G., Phillips, G., 2010. Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies* 65, 46–85.
- Hoberg, G., Phillips, G., 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy* 127, 1423–1465.
- Irvine, P.J., Pontiff, J., 2009. Idiosyncratic return volatility, cash flows, and product market competition. *Review of Financial Studies* 22, 1149–1177.
- Jens, C., 2016. Political uncertainty and investment: Causal evidence from U.S. gubernatorial elections. Unpublished working paper. Tulane University.
- Jenter, D., Lewellen, K., 2015. CEO preferences and acquisitions. *Journal of Finance* 70, 2813–2852.
- Julio, B., Yook, Y., 2012. Political uncertainty and corporate investment cycles. *Journal of Finance* 67, 45–84.
- Julio, B., Yook, Y., 2016. Policy uncertainty, irreversibility, and cross-border flows of capital. *Journal of International Economics* 103, 13–26.
- Jurado, K., Ludvigson, S., Ng, S., 2015. Measuring uncertainty. *The American Economic Review* 105, 1177–1216.
- Kelly, B., Pastor, L., Veronesi, P., 2016. The price of political uncertainty: Theory and evidence from the option market. *Journal of Finance* 71, 2417–2480.
- Kessides, I., 1990. Market concentration, contestability, and sunk costs. *Review of Economics and Statistics* 72, 614–622.
- Kim, H., Kung, H., 2016. The asset redeployability channel: How uncertainty affects corporate investment. *Review of Financial Studies* 30, 245–280.
- La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1998. Law and finance. *Journal of Political Economy* 101, 678–709.

- Maksimovic, V., Phillips, G., 2001. The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains? *Journal of Finance* 56, 2019–2065.
- Mitchell, M.L., Mulherin, J.H., 1996. The impact of industry shocks on takeover and restructuring activity. *Journal of Financial Economics* 2, 193–229.
- Nain, A., Yao, T., 2013. Mutual fund skill and the performance of corporate acquirers. *Journal of Financial Economics* 110, 437–456.
- Offenberg, D., Pirinsky, C., 2015. How do acquires chose between mergers and tender offers? *Journal of Financial Economics* 116, 331–348.
- Officer, M., 2003. Termination fees in mergers and acquisitions. *Journal of Financial Economics* 69, 431–467.
- Ovtchinnikov, A., 2013. Merger waves following industry deregulation. *Journal of Corporate Finance* 21, 51–76.
- Pastor, L., Veronesi, P., 2012. Uncertainty about government policy and stock prices. *Journal of Finance* 67, 1219–1264.
- Pastor, L., Veronesi, P., 2013. Political uncertainty and risk premia. *Journal of Financial Economics* 110, 520–545.
- Phillips, G.M., Zhdanov, A., 2013. R&D and the incentives from merger and acquisition activity. *Review of Financial Studies* 26, 34–78.
- Rhodes-Kropf, M., Viswanathan, S., 2004. Market valuation and merger waves. *Journal of Finance* 59, 2685–2718.
- Rhodes-Kropf, M., Robinson, D.T., Viswanathan, S., 2005. Valuation waves and merger activity: The empirical evidence. *Journal of Financial Economics* 77, 561–603.
- Romalis, J., 2007. NAFTA’s and CUSFTA’s Impact on International Trade, *The Review of Economics and Statistics* 89, 416–435.
- Rossi, S., Volpin, P.F., 2004. Cross-country determinants of mergers and acquisitions. *Journal of Financial Economics* 74, 277–304.
- Sharpe, S., 1994. Financial market imperfections, firm leverage and the cyclicity of employment. *American Economic Review* 84, 1060–1074.
- Sheen, A., 2014. The real product market impact of mergers. *Journal of Finance* 69, 2651–2688.
- Shleifer, A., Vishny, R., 1992. Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance* 47, 1343–1365.
- Shleifer, A., Vishny, R., 2003. Stock market driven acquisitions. *Journal of Financial Economics* 70, 295–311.
- Wang, C., Xie, F., 2009. Corporate governance transfer and synergistic gains from mergers and

acquisitions. *Review of Financial Studies* 22, 829–858.

Yim, S., 2013. The acquisitiveness of youth: CEO age and acquisition behavior. *Journal of Financial Economics* 108, 250–273.

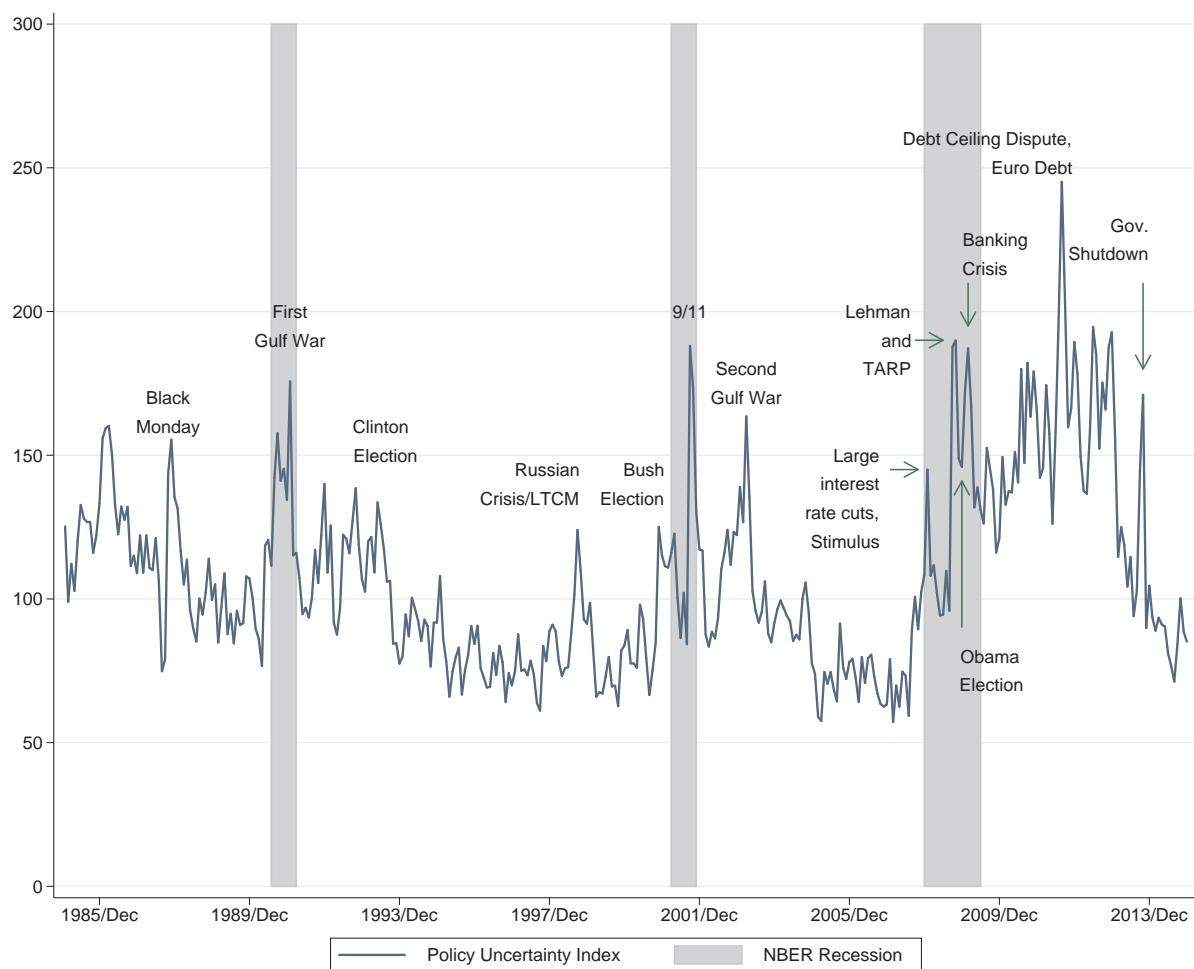


Figure 1
Policy Uncertainty Index

This figure plots the [Baker, Bloom, and Davis \(2016\)](#) index of policy uncertainty (solid line) together with the NBER recession periods (shaded areas) during the January 1985 to December 2014 period.

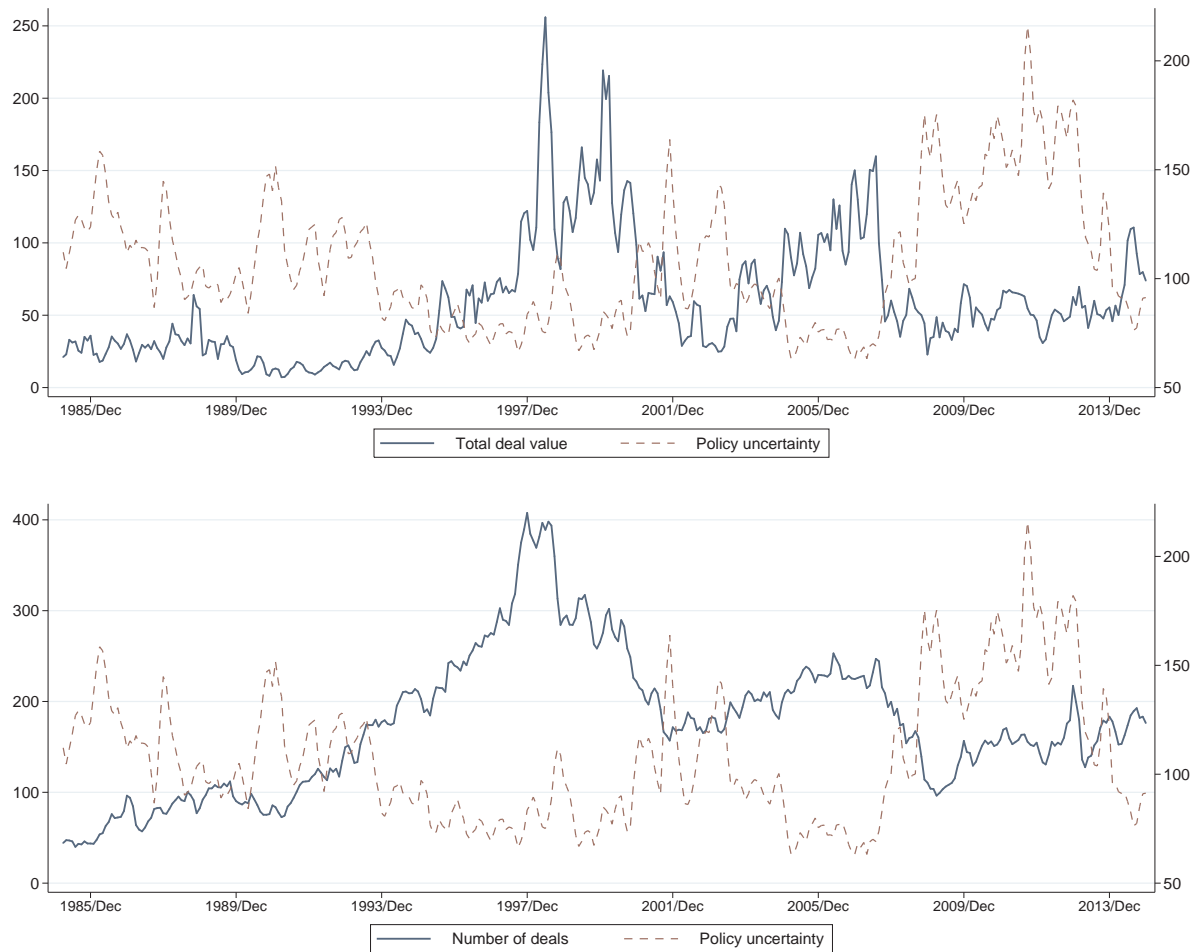


Figure 2

Aggregate Volume and Value of Corporate Acquisitions by U.S. Public Firms

This figure depicts the three-month moving averages of aggregate deal value (top panel) and frequency (bottom panel) of acquisitions conducted by US-based, public firms, together with the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index, from January 1985 to December 2014. Total deal value, reported in billions of 2014 U.S. dollars, and volume correspond to the solid lines and left axes; policy uncertainty corresponds to the dashed lines and right axes.

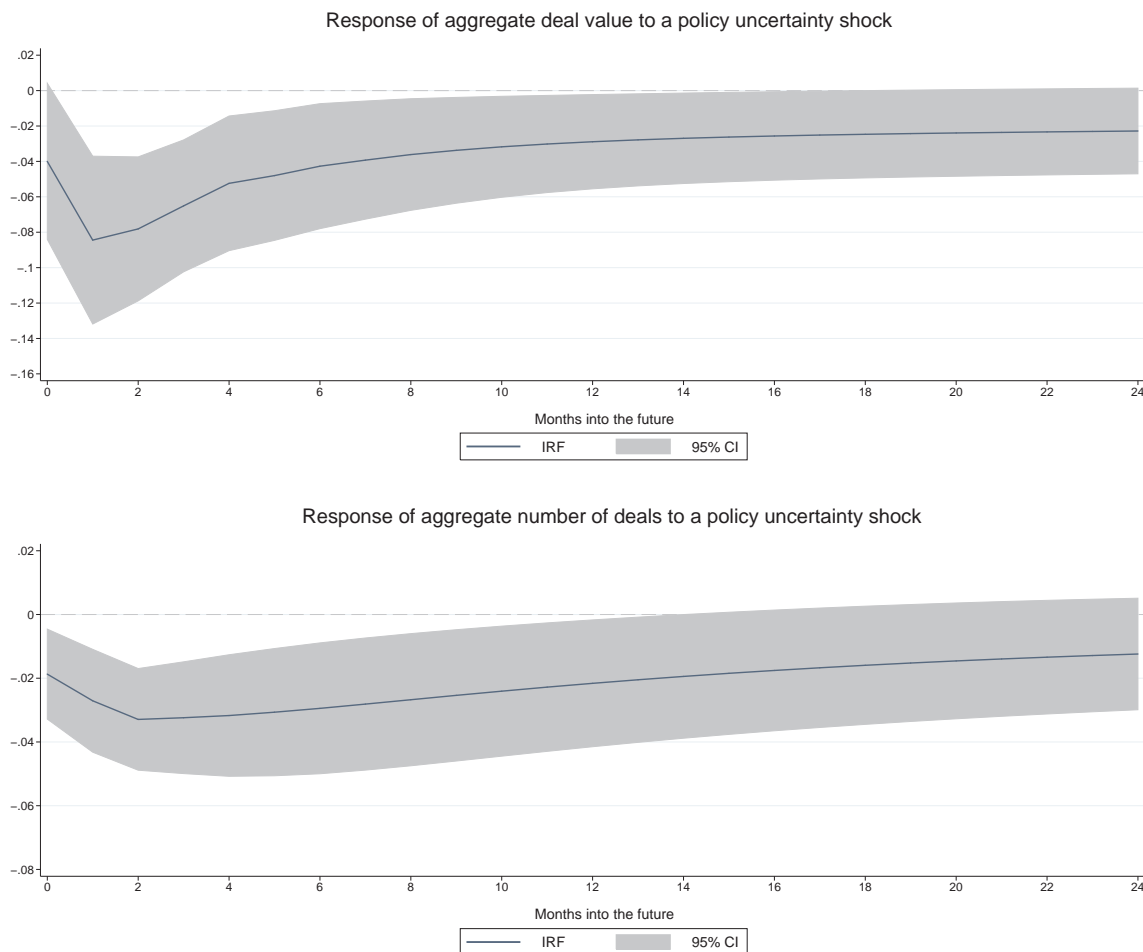


Figure 3

Estimated Effect of a Policy Uncertainty Shock on Acquisitions by U.S. Public Firms

This figure depicts the impulse response function (IRF) of merger and acquisition activity to a shock in the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index. We impose the following ordering on the IRF: policy uncertainty, the VXO implied volatility index, Robert Shiller's CAPE ratio, returns on the volume-weighted CRSP index, the spread on the Baa rate and the risk-free rate, and merger and acquisition activity.

Table 1
The Baker, Bloom, and Davis (2016) Policy Uncertainty Index and its Components

Panel A: Summary statistics					
	Mean	Std. Dev.	P10	Median	P90
Overall policy uncertainty index	107.1	32.77	72.77	99.05	157.5
News component	108.0	39.84	69.69	98.29	162.7
Tax component	243.1	430.0	13.49	19.22	1310.2
Government spending component	99.64	48.55	53.27	88.67	153.1
CPI component	97.70	27.94	68.01	95.22	136.0
Panel B: Correlations					
	Overall index	News component	Tax component	Gov. spending component	
News component	0.883 (0.000)				
Tax component	0.615 (0.000)	0.408 (0.000)			
Government spending component	0.453 (0.000)	0.148 (0.005)	0.0729 (0.167)		
CPI component	0.473 (0.000)	0.136 (0.010)	0.165 (0.002)	0.478 (0.000)	

This table summarizes the Baker, Bloom, and Davis (2016) monthly policy uncertainty index and its four components during our sample period (1985-2014). Panel A presents summary statistics. Panel B presents correlation coefficients and their associated p -values in parentheses.

Table 2
Merger and Acquisition Summary Statistics

	Number of deals	Average annual deal value (in \$ billions)	Average deal size (in \$ millions)	Median deal size (in \$ millions)
Panel A: SDC sample				
All deals	151,925	1,347	266	28
U.S. acquirer	63,100	706	335	41
Public U.S. acquirer	41,050	512	374	41
Panel B: SDC sample merged with CRSP and Compustat				
Public U.S. acquirer	32,286	457	439	52
Public U.S. acquirer and U.S. target	26,680	380	442	51
Public U.S. acquirer and non-U.S. target	5,606	77	425	57

This table presents summary statistics on merger and acquisition announcements reported in the Securities Data Corporation (SDC) database between 1985 and 2014. Panel A covers all SDC observations, while Panel B covers the subset of deals involving acquirers with available data from CRSP and Compustat.

Table 3
Policy Uncertainty and Acquisition Likelihood

	Overall index	News component	Tax component	Gov. spending component	CPI component
Policy uncertainty	-0.702*** (-4.17)	-0.599*** (-2.86)	-0.118** (-2.48)	-0.280** (-2.15)	-0.612*** (-2.84)
Investment opportunities (First principal component)	-0.019*** (-2.58)	-0.028*** (-3.30)	-0.005 (-0.49)	-0.010 (-0.86)	-0.014 (-1.41)
Industry economic shock	0.051*** (3.72)	0.050*** (3.61)	0.025 (1.48)	0.041** (2.50)	0.039** (2.50)
Rate spread	0.151*** (6.94)	0.169*** (4.97)	0.100*** (4.31)	0.122*** (4.68)	0.086*** (4.06)
Shiller's PE ratio	0.023*** (3.84)	0.032*** (5.79)	0.020** (2.45)	0.022*** (3.40)	0.019*** (2.73)
Industry median Q	-0.002 (-0.02)	0.014 (0.16)	0.116 (1.05)	0.095 (0.89)	0.079 (0.75)
Industry median past returns	0.204*** (3.41)	0.200*** (3.56)	0.215*** (3.67)	0.192*** (3.04)	0.224*** (3.56)
Industry σ past returns	-0.033** (-2.17)	-0.038*** (-2.63)	-0.030* (-1.78)	-0.031** (-1.98)	-0.027 (-1.61)
Macroeconomic uncertainty (First principal component)	-0.041*** (-3.47)	-0.050*** (-4.58)	-0.034** (-2.05)	-0.040** (-2.34)	-0.029* (-1.77)
Log total assets	0.282*** (19.30)	0.282*** (19.22)	0.280*** (19.09)	0.281*** (19.16)	0.281*** (19.11)
ROA	0.768*** (9.56)	0.758*** (9.34)	0.749*** (9.55)	0.761*** (9.54)	0.766*** (9.60)
Sales growth	0.336*** (16.47)	0.336*** (16.36)	0.335*** (15.97)	0.335*** (15.91)	0.338*** (16.26)
Book leverage	-0.527*** (-6.15)	-0.525*** (-6.10)	-0.530*** (-6.18)	-0.535*** (-6.25)	-0.536*** (-6.25)
Cash to total assets	0.294*** (4.07)	0.298*** (4.09)	0.301*** (4.33)	0.283*** (3.98)	0.291*** (4.18)
Market-to-book	0.022*** (5.35)	0.022*** (5.31)	0.022*** (5.20)	0.022*** (5.37)	0.022*** (5.32)
Past returns	0.138*** (6.56)	0.139*** (6.67)	0.138*** (6.80)	0.139*** (6.88)	0.135*** (6.57)
Firm-level volatility	-3.481*** (-3.06)	-3.626*** (-3.08)	-3.837*** (-3.21)	-3.524*** (-2.99)	-3.501*** (-3.04)
Time trend	-0.000 (-0.09)	-0.003 (-0.74)	0.019 (1.45)	-0.010* (-1.95)	-0.006 (-1.16)
N	115,796	115,796	115,796	115,796	115,796

This table presents results from logistic regressions of acquisition likelihood on the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index (column 1) and its subcomponents (columns 2-5). Macroeconomic variables are measured as averages over the prior calendar year; all firm-level variables are measured at the end of the prior fiscal year. Detailed variable definitions are in [Appendix A](#). In all models we include Fama-French 48 industry fixed effects and cluster standard errors by firm and year. t -statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 4
Does the Effect of Policy Uncertainty on M&A Activity Reverse Over Time?

	Acquisition Likelihood $_{t+1}$	Acquisition Likelihood $_{t+2}$	Acquisition Likelihood $_{t+3}$	Acquisition Likelihood $_{t+4}$
Policy uncertainty	-0.702*** (-4.17)	-0.592*** (-3.09)	-0.400 (-1.32)	-0.645 (-1.03)
Macro controls	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes
N	115,796	103,939	94,268	83,703

This table presents results from logistic regressions of acquisition likelihood on the overall [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index. The dependent variable equals one if the firm announced an acquisition in year $t+1$, $t+2$, $t+3$, or $t+4$, as noted. All specifications include simultaneous firm-level controls and macroeconomic controls as in Table 3. Detailed variable definitions are in Appendix A. In all models we include Fama-French 48 industry fixed effects and cluster standard errors by firm and year. t -statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 5
Policy Uncertainty and Merger Waves

	Overall index	News component	Tax component	Gov. spending component	CPI component
Policy uncertainty	-4.915*** (-3.01)	-2.650*** (-2.58)	0.114 (0.22)	-2.533* (-1.73)	-2.627*** (-2.58)
Investment opportunities (First principal component)	-0.145 (-0.54)	-0.274 (-1.02)	-0.040 (-0.13)	-0.083 (-0.34)	0.211 (0.69)
Industry economic shock	0.030 (0.58)	0.009 (0.17)	-0.014 (-0.24)	-0.009 (-0.15)	0.008 (0.14)
Rate spread	0.309* (1.93)	0.317* (1.69)	0.145 (0.78)	0.426 (1.63)	-0.047 (-0.27)
Shiller's PE ratio	-0.016 (-0.40)	0.037 (0.85)	0.069 (0.91)	0.014 (0.32)	-0.003 (-0.07)
Industry median Q	-0.960** (-2.27)	-0.850** (-2.22)	-0.543* (-1.76)	-0.562* (-1.65)	-0.605* (-1.84)
Industry median past returns	-0.202 (-0.60)	0.020 (0.06)	0.172 (0.52)	-0.035 (-0.10)	-0.074 (-0.27)
Industry sigma past returns	0.091 (1.10)	0.099 (1.19)	0.126 (1.44)	0.095 (1.01)	0.148* (1.75)
Macroeconomic uncertainty (First principal component)	-0.366 (-1.00)	-0.717* (-1.80)	-0.916* (-1.91)	-0.914** (-2.23)	-0.409 (-1.27)
Industry-level controls	Yes	Yes	Yes	Yes	Yes
N	1,315	1,315	1,315	1,315	1,315

This table presents results from industry-level logistic regressions predicting the start of a merger wave as a function of the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index. We include simultaneous controls for investment opportunities, valuation waves and general economic uncertainty described in Appendix A. Macroeconomic variables are measured at the end of the prior calendar year; all other variables are measured at the end of the prior fiscal year. In all models we include control variables from Table 3, averaged at the industry level; we cluster standard errors by industry and year. *t*-statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 6
Investment Irreversibility and Target Competition

Panel A: Investment irreversibility						
	Capital intensity	Asset redeployability	Sunk cost index	Durable industries		
Policy uncertainty	-0.300*** (-3.91)	-0.476*** (-5.65)	-0.399*** (-3.34)	-0.428*** (-7.27)		
Macro & firm controls	Yes	Yes	Yes	Yes		
N	115,796	115,796	115,796	115,796		
Panel B: The option to delay						
	Herfindahl	Concentration ratio				Deal volume
		Top 4	Top 8	Top 20	Top 50	
Policy uncertainty	-0.498*** (-6.51)	-0.853* (-1.70)	-0.876* (-1.73)	-0.912* (-1.72)	-0.866* (-1.67)	-0.337*** (-2.97)
Macro & firm controls	Yes	Yes	Yes	Yes	Yes	Yes
N	115,796	115,796	115,796	115,796	115,796	115,796

This table explores the cross-sectional heterogeneity in the relation between policy uncertainty and M&A activity through the real options channel. All regressions are second stage probits from Heckman selection models. In Panel A dependent variables equal one if the firm announces an acquisition of a target representing a more irreversible investment; in Panel B dependent variables equal one if the firm announces an acquisition of a target from an industry with low competition (either high concentration or low M&A deal volume). The first stage (not shown) predicts the likelihood of announcing an acquisition, as in first model in Table 3 with the addition of a proxy for hypothetical mechanical mutual funds outflows to the firm, calculated following [Edmans, Goldstein, and Jiang \(2012\)](#). All specifications include simultaneous acquirer firm-level controls and macroeconomic controls for as in Table 3. Detailed variable definitions are in Appendix A. In all models we cluster standard errors by acquirer and year. We include Fama-French 48 industry fixed effects in the acquisition likelihood logits. *t*-statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 7
Acquirer Competition and Policy Uncertainty Exposure

	Option to Delay		Policy Uncertainty Exposure	
	TNIC Herfindahl	Deal volume	Government sensitivity	Return sensitivity
Policy uncertainty	-0.080 (-0.68)	-0.611*** (-4.62)	-0.557*** (-3.11)	-0.703*** (-4.21)
Policy uncertainty x Independent variable	-0.388** (-2.57)	2.892*** (3.57)	-0.781*** (-2.87)	-3.568*** (-2.89)
Independent variable	1.579** (2.27)	-5.317 (-1.44)	3.393*** (2.62)	15.924*** (2.79)
Macro & firm controls	Yes	Yes	Yes	Yes
N	73,472	114,613	90,391	115,796

This table explores the cross-sectional heterogeneity in the relation between policy uncertainty and M&A activity through the real options channel. All regressions are logistic regressions of acquisition likelihood on the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index, including proxies for the option to delay the acquisition or for policy uncertainty exposure, and interactions of these proxies with policy uncertainty. All specifications include simultaneous firm-level controls and macroeconomic controls for as in Table 3. Detailed variable definitions are in Appendix A. In all models we cluster standard errors by acquirer and year. We include Fama-French 48 industry fixed effects in the acquisition likelihood logits. *t*-statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 8
Policy Uncertainty and Interim Risk

	Low Policy Uncertainty	High Policy Uncertainty	High-Low
Interim duration (days)	65.34	70.87	5.53 [0.4631]
Number of tender offers	125.6	87.79	-37.81** [0.0308]
Percentage of deals with public targets	12.17	12.23	0.07 [0.8958]

This table presents mean interim duration, tender offer deal volume, and the percentage of deals involving public targets, segmented on the level on policy uncertainty. “Low” (“high”) policy uncertainty implies that the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index was below (above) its median value during our sample period. Interim duration is the number of days from deal announcement to completion. The number of tender offers is the annual average deal volume of tender offers. Percentage of deals with public targets is the percentage of total acquisitions involving publicly traded targets. We conduct difference in means tests and present the associated p -values below in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 9
Policy Uncertainty versus Market-wide Volatility

Panel A: Predicting one-month-ahead M&A activity									
	All	Public targets	Private targets	Subsidiary	All	Public targets	Private targets	Subsidiary	Subsidiary
% Δ VIX	-0.044 (-0.90)	-0.287** (-2.14)	0.021 (0.33)	-0.076 (-1.55)					
					-0.058 (-1.19)	-0.293** (-2.16)	0.001 (0.02)	-0.082 (-1.56)	
% Δ Policy uncertainty					0.057 (0.70)	-0.010 (-0.08)	0.098 (0.97)	0.017 (0.26)	0.028 (0.42)
N	286	286	286	286	286	286	286	286	286
Panel B: Predicting 12-months-ahead M&A activity									
	All	Public targets	Private targets	Subsidiary	All	Public targets	Private targets	Subsidiary	Subsidiary
% Δ VIX	-0.041 (-0.86)	0.068 (0.95)	-0.072 (-1.23)	-0.028 (-0.89)					
					0.005 (0.10)	0.120* (1.73)	-0.021 (-0.35)	0.005 (0.14)	
% Δ Policy uncertainty					-0.159*** (-4.61)	-0.127** (-2.00)	-0.193*** (-4.30)	-0.108*** (-4.34)	-0.105*** (-3.40)
N	276	276	276	276	286	286	286	276	276

This table presents macro-level regressions modeling the monthly (Panel A) and yearly (Panel B) percentage change in merger and acquisition deal volume as a function of corresponding percentage changes in market-wide volatility (the VIX index) and the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index news component. In all models we control for monthly or yearly percentage changes in Shiller's PE ratio, market returns, rate spread and cash, and correct standard errors for auto-correlated using the Newey-West procedure with 12 lags. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 10
Policy Uncertainty and Deal Quality

	Low Policy Uncertainty	High Policy Uncertainty	Low - High
CAR _[-1,1]	0.0127*** (8.80)	0.0147*** (9.25)	-0.002 [0.3494]
CAR _[-2,2]	0.0135*** (7.23)	0.0169*** (9.66)	-0.0034 [0.1859]
Change in ROA	-0.0260*** (-5.26)	-0.0239*** (-4.70)	-0.0021 [0.7747]
Change in Sales Growth	-0.00223 (-0.17)	0.0146 (0.94)	-0.0168 [0.4031]

This table presents bidder announcement returns and post-acquisition operating performance and sales growth, segmented on level on policy uncertainty. “Low” (“high”) policy uncertainty implies that the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index was below (above) its median value during our sample period. Bidder announcement returns are the cumulative 3-day or 5-day stock returns to the bidder net the return to the value-weighted CRSP index over the same period. Operating performance (sales growth) is measured as the change in industry-adjusted ROA (industry-adjusted sales) from the year prior to the acquisition to the year following the acquisition. *t*-statistics are reported in parentheses. We conduct difference in means tests and present the associated *p*-values below in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 11
Policy Uncertainty, Corporate Governance, and CEO Characteristics

	Total ownership by top 5 institutions	# Blockholders > 10% ownership	# Analysts	% Independent directors	Entrenchment index	CEO pay slice	CEO vega	CEO delta	CEO overconfidence
Policy uncertainty	-0.308** (-2.28)	-0.382*** (-2.99)	-0.740*** (-3.78)	-0.195 (-1.21)	-0.086 (-0.59)	-0.226 (-1.43)	-0.162 (-0.81)	-0.151 (-0.83)	-0.089 (-0.43)
Policy uncertainty x Independent variable	-0.030 (-1.35)	0.051 (0.74)	0.003 (0.30)	-0.001 (-0.04)	-0.057 (-1.21)	-0.001 (-0.06)	-0.018 (-0.82)	-0.020 (-0.88)	-0.029 (-1.35)
Independent variable	0.015 (0.15)	-0.253 (-0.80)	-0.007 (-0.16)	0.012 (0.16)	0.298 (1.36)	0.029 (0.39)	0.112 (1.09)	0.110 (1.03)	0.169* (1.71)
Macro & firm controls	Yes 90,681	Yes 90,681	Yes 115,796	Yes 24,351	Yes 28,593	Yes 28,174	Yes 27,364	Yes 27,364	Yes 25,063
N									

This table presents results from logistic regressions modeling the likelihood of announcing an acquisition in year $t+1$ as a function of firm and industry characteristics measured at time t . Each column uses a different measure of corporate governance (first six columns) or CEO characteristic (last three columns) as an additional control ("Independent variable") in our baseline specification. Our tests also control for the interaction between each of these variables and the overall [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index. All other control variables are identical to our baseline specification from Table 3. In all models we include Fama-French 48 industry fixed effects and cluster standard errors by firm and year. t -statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 12
Policy Uncertainty and Risk Management

Dependent variable	Second-stage Heckman Logit	
	Domestic target	Vertical merger
Policy uncertainty	-0.286*** (-2.76)	0.332*** (5.81)
Macro controls	Yes	Yes
Firm-level controls	Yes	Yes
N	115,796	115,796

This table explores the relation between policy uncertainty and risk-management motivated M&A activity. The regressions are second stage logits from Heckman selection models predicting whether the target is a domestic (US) firm and whether the merger is vertical, as a function of the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index and acquirer-level or macro-level controls. The first stage (not shown) predicts the likelihood of announcing an acquisition, as in first model in [Table 3](#) with the addition of a proxy for hypothetical mechanical mutual funds outflows to the firm, calculated following [Edmans, Goldstein, and Jiang \(2012\)](#). Control variables are described in [Appendix A](#). Macroeconomic variables are measured at the end of the prior calendar year; all other variables are measured at the end of the acquirer's prior fiscal year. In all models we include all control variables from [Table 3](#) and cluster standard errors by acquirer and year. *t*-statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 13
Which Policies Matter Most?

	Fiscal policy	Taxes	Gov. spending	Monetary policy	Regulation	Financial regulation	Health care	Entitlement programs	National security	Trade policy	Sovereign debt
Policy uncertainty	-0.323*** (-3.53)	-0.336*** (-3.40)	-0.176*** (-3.17)	-0.379** (-2.21)	-0.159* (-1.69)	-0.282*** (-6.14)	-0.056 (-0.54)	-0.071 (-0.65)	-0.201 (-1.43)	0.071 (1.09)	-0.041 (-1.10)
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	115,796	115,796	115,796	115,796	115,796	115,796	115,796	115,796	115,796	115,796	115,796
Percent of total policy uncertainty	46.1%	40.3%	17.1%	28.1%	17.4%	3.3%	17.3%	12.4%	23.8%	3.8%	1.6%

This table presents results from logistic regressions of acquisition likelihood on the subcomponents of the Baker, Bloom, and Davis (2016) policy uncertainty index news component. A list of the search terms used to create these subcomponents can be found at: http://www.policyuncertainty.com/categorical_terms.html. All specifications include simultaneous firm-level controls and macroeconomic controls for as in Table 3. Detailed variable definitions are in Appendix A. In all models we include Fama-French 48 industry fixed effects and cluster standard errors by firm and year. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 14
Deal Characteristics and Policy Uncertainty

Dependent variable	Deal premium	Termination fee amount	Termination fee indicator	MAC Exclusions
Policy uncertainty	0.129*** (2.71)	-0.617*** (-2.63)	-0.489*** (-2.68)	9.406*** (3.47)
Macro controls	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes
N	102,202	115,796	115,796	31,214

This table explores the relation between policy uncertainty and M&A deal characteristics. All regressions are second stage Heckman models or Heckman logits in the case of binary dependent variables. The first stage (not shown) predicts the likelihood of announcing an acquisition, as in the first model in Table 3, with the addition of a proxy for hypothetical mechanical mutual funds outflows to the firm, calculated following [Edmans, Goldstein, and Jiang \(2012\)](#). Deal premium is deal value scaled by the target's market capitalization four weeks prior to the announcement, which is adjusted if the percentage of the target acquired is less than 100%. Termination fee amount is a continuous variable equal to the dollar value of the target's termination fee. Termination fee indicator equals zero (one) if the target has a zero (non-zero) termination fee. MAC exclusions are the number of material adverse clause exclusions in the contract. Control variables are described in Appendix A. Macroeconomic variables are measured at the end of the prior calendar year; all other variables are measured at the end of the acquirer's prior fiscal year. In all models we include all control variables from Table 3 and cluster standard errors by acquirer and year. We include Fama-French 48 industry fixed effects in the acquisition likelihood logit. *t*-statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

A. Appendix A: Variable Definitions

Below we describe the calculation of the main control variables used in this study.

A.1. Proxies for investment opportunities, valuation waves, and general economic uncertainty

- **Investment opportunities (first principal component)**: the first principal component of the following four variables. We use quarterly averages of these variables throughout our analysis. Consequently, this principal component measure is also measured at a quarterly frequency.
 1. **Consumer confidence**: the monthly, survey-based index of consumer confidence developed by the University of Michigan (available at <http://www.sca.isr.umich.edu/>).
 2. **Leading economic indicator**: a proprietary index developed by the Conference Board to measure future economic activity based on 11 leading economic indicators that have been found to have significant predictive power over future GDP growth.
 3. **CFNAI**: the Chicago Fed National Activity Index (available at <https://www.chicagofed.org/research/data/cfnai/historical-data>), which is designed to measure current economic activity and inflationary pressure based on 85 monthly economic indicators.
 4. **Expected GDP growth**: the average one-year-ahead GDP forecast from the bi-annual Livingstone Survey of Professional Forecasters (data is available from the Philadelphia FED).
- **Industry economic shock**: following Harford (2005), the first principal component from economic-shocks to each industry’s operating environment, calculated separately for each industry using the following seven firm-level indicators: net income to sales (IB/SALE), sales to assets (SALE/AT), R&D to assets (XRD/AT), capital expenditures to assets (CAPX/AT), employment growth (percentage change in item EMP), return on assets (IB/AT) and sales growth (percentage change in item SALE). For each of the 48 industries in the Fama and French (1997) classification, each year, we take the industry median of the absolute (annual) change in each of the above variables.
- **Rate spread**: following Garfinkel and Hankins (2011), we proxy for market liquidity using the spread between Baa rated bonds and the Federal Funds rate (data is available from the St. Louis FED). To match the annual frequency of the firm-level data, we use calendar-year averages of this (monthly) spread variable.
- **Shiller’s PE ratio**: the Cyclically Adjusted Price Earnings Ratio (CAPE) developed by Robert Shiller (available at <http://www.econ.yale.edu/~shiller/data.htm>).
- **Industry median Q**: the annual, median value of Tobin’s q for each one of the Fama and French (1997) 48 industries. Tobin’s q is measured as book value of assets (Compustat annual item AT) minus book value of equity (see Section A.2) plus market value of equity (item PRCC.F times item CSHO), all divided by book value of assets.
- **Industry median past returns**: the annual median of firm-level 36-month cumulative returns for each of the Fama and French (1997) 48 industries. Each calendar year t , we calculate each firm’s cumulative returns using the 36 months leading up to the last month of the fiscal year ending in t .
- **Industry σ past returns**: the annual median of firm-level 36-month return volatility for each of the Fama and French (1997) 48 industries. Each calendar year t , we calculate the standard deviation of each firm’s returns, using the 36 monthly return observations leading up to the last month of the fiscal year ending in t .

- **Macroeconomic uncertainty (first principal component):** the principal component extracted from the following four variables. We use quarterly averages of these variables throughout our study, so this principle component variable also has a quarterly frequency.
 1. **JLN uncertainty index:** monthly index of macroeconomic uncertainty developed by Jurado, Ludvigson and Ng (2015) as the unforecastable component in a system of 279 macroeconomic variables.
 2. **VXO index:** daily index of implied volatility released by the Chicago Board Options Exchange, calculated based on trading of S&P 100 options.
 3. **CS σ past returns:** the cross-sectional standard deviation of cumulative returns from the past three months, calculated each month, using the entire CRSP universe.
 4. **CS σ past sales growth:** the cross-sectional standard deviation of year-on-year sales growth (percentage change in the Compustat quarterly item SALEQ), calculated each calendar quarter, using the entire Compustat quarterly universe.

Table A1
Summary Statistics for Macroeconomic Variables

	Mean	Std. Dev.	P10	Median	P90
Consumer confidence (annual log change)	0.165	0.048	0.124	0.156	0.212
Leading economic indicator	0.175	0.054	0.104	0.173	0.238
CFNAI	20.800	8.503	12.290	18.940	30.130
Expected GDP growth	-0.005	0.121	-0.159	0.004	0.121
Rate spread	0.960	0.055	0.908	0.956	1.012
Shiller's PE ratio	0.019	0.060	-0.071	0.035	0.071
JLN uncertainty index	-0.104	0.819	-1.057	0.005	0.696
VXO index	0.064	0.015	0.050	0.064	0.080
CS σ past returns	3.874	1.709	1.720	4.030	5.920
CS σ past sales growth	23.870	7.319	15.250	22.660	34.710

This table presents summary statistics for our macroeconomic indicators during our sample period (1985-2014).

Table A2
Correlations between macroeconomic variables

	Policy uncertainty	Consumer confidence	Leading econ. ind.	CFNAI	Expected GDP growth	Rate spread	Shiller's PE ratio	JLN index	VXO	CS σ past returns
Consumer confidence (annual log change)	-0.185 (0.001)									
Leading econ. Indicator	-0.241 (0.000)	0.516 (0.000)								
CFNAI	-0.352 (0.000)	0.456 (0.000)	0.757 (0.000)							
Expected GDP growth	-0.293 (0.000)	0.145 (0.007)	0.291 (0.000)	0.342 (0.000)						
Rate spread	0.539 (0.000)	0.0194 (0.720)	-0.162 (0.003)	-0.280 (0.000)	-0.266 (0.000)					
Shiller's PE ratio	-0.442 (0.000)	0.0639 (0.237)	0.109 (0.043)	0.155 (0.004)	-0.0533 (0.324)	-0.307 (0.000)				
JLN uncertainty index	0.305 (0.000)	-0.488 (0.000)	-0.762 (0.000)	-0.667 (0.000)	-0.252 (0.000)	0.214 (0.000)	-0.149 (0.006)			
VXO index	0.397 (0.000)	-0.391 (0.000)	-0.498 (0.000)	-0.419 (0.000)	-0.235 (0.000)	0.267 (0.000)	0.00300 (0.956)	0.585 (0.000)		
CS σ past returns	0.144 (0.007)	-0.0671 (0.214)	-0.519 (0.000)	-0.380 (0.000)	-0.129 (0.016)	0.306 (0.000)	0.135 (0.012)	0.457 (0.000)	0.334 (0.000)	
CS σ past sales growth	0.354 (0.000)	-0.101 (0.062)	-0.336 (0.000)	-0.318 (0.000)	-0.279 (0.000)	0.467 (0.000)	-0.127 (0.018)	0.477 (0.000)	0.346 (0.000)	0.295 (0.000)

This table presents correlation coefficients for our macroeconomic indicators and their associated p -values (in parentheses) during our sample period (1985-2014).

A.2. Firm-level controls

All firm-level variables are measured using data from the COMPUSTAT annual database from January 1985 to December 2014. We winsorize each variable at the 1st and 99th percentiles.

- **Log total assets:** natural logarithm of total assets (Compustat annual item AT), measured in 2001 U.S. dollars.
- **ROA:** return on assets, measured as income before extraordinary items (Compustat annual item IB) plus interest expense (item XINT) plus income taxes (item XINT), all divided by total assets (item AT).
- **Sales growth:** percentage change in sales (Compustat annual item SALE).
- **Book leverage:** long term debt (Compustat annual item DLTT) plus debt in current liabilities (item DLC), all divided by total assets (item AT).
- **Cash to total assets:** cash and short-term investments (Compustat item CHE) divided by total assets (item AT).
- **Market-to-book:** market value of equity divided by book value of equity. Market value of equity is share price (Compustat annual item PRCC_F) times common shares outstanding (item CSHO). Book value of equity is shareholders' equity (item SEQ) minus preferred stock plus deferred taxes (item TXDITC). We measure preferred stock using liquidation value (item PSTKL), redemption value (item PSTKR) or carrying value (item PSTK) in this order, depending on availability. If SEQ is missing, we measure book value of equity as common equity (item CEQ) plus carrying value of preferred stock (item PSTK). Finally, if CEQ is missing, we measure book value of equity as total assets (item AT) minus total liabilities (item LT).
- **Past returns:** cumulative returns during the 12 month period ending at the end of the firm's fiscal year. This is measured using monthly returns from the CRSP monthly database.
- **Firm-level volatility:** the standard deviation of the firm's daily returns from month $t-13$ to $t-2$, following [Bhagwat, Dam, and Harford \(2016\)](#).

Table A3
Summary Statistics for Firm-Level Variables

	Mean	Std. Dev.	P10	Median	P90
Panel A: Acquirers					
Log total assets	6.672	2.161	3.909	6.602	9.628
ROA	0.053	0.166	-0.066	0.076	0.188
Sales growth	0.266	0.547	-0.092	0.132	0.700
Book leverage	0.196	0.180	0.000	0.160	0.449
Cash to total assets	0.170	0.193	0.011	0.088	0.467
Market-to-book	3.202	3.507	0.980	2.148	6.111
Past returns	0.327	1.018	-0.350	0.163	1.000
Firm-level volatility	0.032	0.019	0.015	0.028	0.056
Number of observations	16,205				
Panel B: Non-acquirers					
Log total assets	5.647	2.140	2.903	5.557	8.498
ROA	0.005	0.213	-0.210	0.046	0.175
Sales growth	0.176	0.516	-0.173	0.082	0.511
Book leverage	0.203	0.192	0.000	0.160	0.479
Cash to total assets	0.165	0.202	0.009	0.080	0.469
Market-to-book	2.758	3.635	0.667	1.655	5.479
Past returns	0.149	0.920	-0.536	0.031	0.798
Firm-level volatility	0.039	0.023	0.016	0.033	0.070
Number of observations	99,591				
Panel C: All firms					
Log total assets	5.791	2.172	3.000	5.707	8.690
ROA	0.012	0.208	-0.191	0.051	0.177
Sales growth	0.188	0.521	-0.164	0.089	0.539
Book leverage	0.202	0.191	0.000	0.160	0.475
Cash to total assets	0.166	0.201	0.009	0.081	0.468
Market-to-book	2.820	3.620	0.697	1.723	5.602
Past returns	0.174	0.936	-0.518	0.051	0.827
Firm-level volatility	0.038	0.023	0.016	0.032	0.068
Number of observations	115,796				

This table presents summary statistics at the firm-year level for acquiring (Panel A), non-acquiring (Panel B), and all (Panel C) firm-years between 1985 and 2014. A firm is defined as an acquirer in fiscal year t if it announces an acquisition that year. Our full sample covers 14,008 unique firms, of which 7,006 announce an acquisition at least once. Variables, measured in year $t-1$, are defined in Appendix A.

A.3. Target-level investment irreversibility, competition, and country of origin

- **Capital intensity ratio:** The median of the property, plant and equipment (PP&E) to total assets ratio for each Fama-French 48 industry. PP&E and total assets are from Compustat.
- **Asset redeployability:** From the 1997 BEA capital flows table, we first compute the asset redeployability score for each asset category as the percentage of the industries using it. We then calculate the weighted average of the category-level asset redeployability measured at the industry level, with weights equaling the asset category's percentage of total industry capital expenditures.
- **Sunk costs:** An indicator variable equal to one if the target Fama-French 48 industry has high sunk costs. We first create the following measures: rent expense, depreciation expense, and PP&E sales over the prior 12 quarters, all scaled by lagged PP&E. Next, we calculate the Fama-French 48 industry average of each measure. This variable equals zero if all three industry proxies are above the median, and one if at least one of the industry proxies falls below the median.

- **Durable goods industry:** An indicator variable equal to one if the target Fama-French 48 industry is classified as a durable goods industry, based on the SIC codes in each industry.
- **Herfindahl:** An indicator equal to one if the target Fama-French 48 industry has an above-median Compustat sales-based Herfindahl index. A high Herfindahl index corresponds to high concentration, implying low competition.
- **Concentration ratio:** An indicator equal to one if the target industry's has an above-median concentration ratio based on data from the U.S. Census Bureau. Concentration ratios are defined as the top 4, 8, 20, or 50 firms' sales divided by total industry sales. A high concentration ratio implies low competition.
- **Deal volume:** An indicator equal to one if the frequency of deals in the target's Fama-French 48 industry over the prior calendar year is *below* the median. Low deal volume corresponds to low competition.
- **Domestic target:** An indicator variable equal to one if the target is domestic and zero if the target is foreign.

A.4. Acquirer interactions

- **TNIC Herfindahl:** The sales-based Herfindahl index calculated for the [Hoberg and Phillips \(2016\)](http://hobergphillips.usc.edu) text-based network industry classifications (TNIC), which uniquely assign product market competitors to individual firms each year. See the Hoberg-Phillips Data Library at: <http://hobergphillips.usc.edu>. A high Herfindahl index corresponds to high concentration, implying low competition.
- **Deal volume:** The frequency of deals in the acquirer's Fama-French 48 industry over the prior calendar year. High deal volume corresponds to high competition.
- **Government sensitivity:** The percentage of industry sales to government entities. Using the Benchmark Input-Output (I-O) Accounts table published by the Bureau of Economic Analysis (BEA), we estimate x_i/y_i where x_i represents total direct or indirect input necessary from industry i to meet government demand and y_i represents industry i 's total output. Industry level government spending can be calculated from the industry-by-commodity table in the I-O accounts as follows:

$$x_i = \sum_j a_{i,j} g_j, \quad (4)$$

where $a_{i,j}$ is the value of input from industry i necessary to produce \$1 of industry j 's output and g_j is the value of output from industry j sold directly to the government at the federal, state, or local level. I-O accounts begin in 1982 and are updated every five years; we update our measure accordingly. We merge our measure of dependence on government spending on three-digit SIC code (prior to 2002) or NAICS codes with the use of the BEA concordance tables. If multiple industry codes in the I-O accounts correspond to the same three-digit SIC or NAICS code, we calculate a weighted average of the industry dependencies on government spending, with the weights being a function of total industry outputs.

- **Return sensitivity:** Ex-ante industry-level stock return sensitivity to policy uncertainty. Specifically, we use the t -statistic of the coefficient associated with policy uncertainty (p_i) in the following regression, run over the 60 months prior to the beginning of the firm's fiscal year in which we measure acquisition announcements:

$$R_{i,t} - R_{f,t} = a_i + p_i BBD_t + b_i(R_{M,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + e_{i,t}, \quad (5)$$

where $R_{i,t}$ is the value-weighted return on industry i in month t , $R_{f,t}$ is the risk-free rate

(1-month U.S. T-bill rate), BBD_t is the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index, $R_{M,t}$ is the return on the market (value-weighted portfolio of NYSE, Amex, and NASDAQ stocks), and SMB_t and HML_t are the size and value returns of [Fama and French \(1993\)](#).

Online Appendix to

“Does Policy Uncertainty Affect Mergers and Acquisitions?”

This appendix contains additional tests omitted from the main text for brevity.

1. Alternative specifications and endogeneity concerns

We verify the robustness of our baseline Table 3 result that policy uncertainty is significantly negatively related to acquisition likelihood. First, we show that the negative relation holds when including macroeconomic controls individually. Tables B1, B2, and B3 present controls for investment opportunities, valuation waves, and general economic uncertainty, respectively. The policy uncertainty coefficient remains negative and significant in all models. Moreover, many macroeconomic controls become insignificant in regressions with policy uncertainty. For example, three of the four valuation wave proxies and half of the other uncertainty proxies have significant explanatory power on their own but not in models including policy uncertainty.

Next, to address the possibility that an omitted variable bias remains present in our tests, we propose several plausibly exogenous instruments for policy uncertainty in Table B4. First, we use the Azzimonti (2016) partisan-conflict index from the Federal Reserve Bank of Philadelphia, which is based on a frequency count of newspaper articles containing terms related to lawmakers’ policy disagreement. Second, similar in spirit to Julio and Yook (2016) we use two variables that measure the political uncertainty generated by gubernatorial elections based on data from the Congressional Quarterly Press Electronic Library. In the first stage, we regress the Baker, Bloom, and Davis (2016) index on each instrument, the macroeconomic controls used in our main specification from Table 3, as well as annual averages of the firm-level controls used in our previous tests. In the second stage, we run the same logistic regressions from Table 3, only this time using the fitted values from the first stage regressions as the policy uncertainty variable. F-statistics from the first stage regressions suggest that all our instruments satisfy the relevance condition. Across all specifications, we find that the negative relation between policy uncertainty and acquisition likelihood remains significantly negative. This result, combined with our extensive set of controls, helps alleviate endogeneity concerns.

2. Deregulation

We examine how deregulation events and idiosyncratic volatility relate to M&A activity. We identify deregulation events as the union of deregulation events from [Harford \(2005\)](#) and [Ovtchinnikov \(2013\)](#) that occur during our sample period. We examine acquisition likelihood in year $t + 1$ as a function of policy uncertainty, deregulation, and macro- and firm-level controls in year t . Since [Irvine and Pontiff \(2009\)](#) show that deregulation is generally followed by an increase in idiosyncratic volatility (which could impact mergers), we explicitly control for the change in idiosyncratic volatility around the deregulation event (from year t to $t + 1$). We also control for total volatility in year t (as in all models in the paper) to account for firm-level risk during deregulation.

Table [B5](#) shows that, indeed, deregulation events are followed by upticks in merger activity on average. This result holds with (Model (1)) or without (Model (3)) controls for policy uncertainty. Model (2) and (4) are analogous except we condition on whether or not idiosyncratic volatility actually decreased after the regulation (from year t to $t + 1$). Our estimates show that the effect of deregulation on mergers is significantly greater in cases where idiosyncratic volatility decreased post-deregulation.

In Table [B6](#) we examine the effect of changes in regulatory uncertainty in general (as opposed to restricting ourselves to deregulation events). We use the BBD regulation and financial regulation indices to identify spikes in uncertainty related to regulation. To identify significant spikes in regulatory uncertainty, we construct an indicator variable (Regulatory policy uncertainty spike) which equals one if, within the calendar year, the BBD regulation (Models (1)-(4)) or financial regulation (Models (5)-(8)) jumps to at least two standard deviations above the mean and falls back below the mean (i.e., policy uncertainty was resolved). Whether or not we control for policy uncertainty, we see that regulatory uncertainty spikes differentially affect firms with decreases in idiosyncratic volatility, with mergers becoming more likely if idiosyncratic volatility falls after the regulatory spike. The results suggest that a decline in idiosyncratic volatility is associated with a subsequent increase in M&A activity.

Finally, it is important to note that the effect of the overall BBD policy uncertainty index on acquisition likelihood remains consistently negative and significant, even after controlling for various regulatory events.

Overall, the results in Tables B5 and B6 confirm that decreases in regulatory uncertainty are followed by increases in merger activity and that this relation is moderated by the effects of deregulation on idiosyncratic risk. It is important to note that Irvine and Pontiff (2009) find that deregulation increases idiosyncratic volatility on average, which should decrease merger activity. This seems to be inconsistent with the prior findings that deregulation events are followed by increased merger activity (e.g., Mitchell and Mulherin, 1996). Our results offer a potential resolution for these opposing findings: While deregulation could increase idiosyncratic volatility on average, it could in fact decrease firm-level risk for some firms (e.g., some incumbents could be expected to benefit from deregulation). If this is the case, we should see a positive relation between deregulation and future merger activity only for the firms that experience reduced idiosyncratic volatility post-deregulation, which is what we find in Table B6.

3. Competition and types of policy uncertainty

In Table B7 we rerun the acquisition likelihood model in Table 7, replacing the overall BBD index with its four components (news, tax, government spending and CPI) in Panel A and with the subcomponents of the news in Panel B. The interactive effect of competition with policy uncertainty is strongest for the government spending and news components, and for news subcomponents capturing taxes, government spending, monetary and fiscal policy, regulation (overall and financial), health care and entitlement.

4. Likelihood of acquiring a private target

In Table B8 we rerun the acquisition likelihood model in Table 3 for private-target acquisitions only. The overall BBD index and each of the four subcomponents (news, tax, government spending and CPI) have a significant negative effect on the likelihood of acquiring a private target.

5. Method of payment

Prior policy uncertainty literature (e.g., Julio and Yook, 2012) finds that firms tend to increase cash holdings when policy uncertainty increases. Thus, in Table B9 we examine the relation between policy uncertainty and merger payment method (cash or stock). The results suggest that higher policy uncertainty is associated with an increased likelihood of stock financing for firms that are least likely to be overvalued, consistent with the idea that firms hoard cash during uncertain times (as in Julio and Yook (2012)) but are less able to do so if they are overvalued.

Table B1
Controlling for Investment Opportunities and Economic Conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Policy uncertainty	-0.690*** (-3.88)	-0.656*** (-4.03)	-0.615*** (-3.17)	-0.690*** (-4.03)	-0.690*** (-3.92)	-1.125*** (-5.09)						
Consumer confidence	0.574* (1.86)						0.576 (1.60)					
Leading econ. Indicator		2.072*** (2.85)						2.314*** (3.48)				
CFNAI			0.083* (1.93)						0.143*** (3.88)			
Expected GDP growth				-8.230* (-1.72)						-8.727 (-1.18)		
Industry economic shock					0.029 (1.12)						0.036 (1.55)	
Rate spread						0.101*** (2.84)						-0.021 (-0.61)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	115,796	115,796	115,796	115,796	115,796	115,796	115,796	115,796	115,796	115,796	115,796	115,796

This table presents results from logistic regressions of acquisition likelihood on the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index, including controls for investment opportunities, described in Appendix A. Macroeconomic variables are averaged over the prior calendar year; all other variables are measured at the end of the prior fiscal year. In all models we include all firm-level control variables from Table 3 and Fama-French 48 industry fixed effects; we cluster standard errors by firm and year. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table B2
Controlling for Valuation Waves

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy Uncertainty	-0.519** (-2.46)	-0.595*** (-3.13)	-0.600*** (-3.64)	-0.657*** (-3.76)				
Shiller's PE ratio	0.010 (1.26)				0.020*** (2.79)			
Industry median Q		0.223 (1.64)				0.488*** (3.20)		
Industry median past returns			0.255*** (3.52)				0.331*** (5.08)	
Industry sigma past returns				0.031 (1.02)				0.058* (1.90)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	115,796	115,796	115,796	115,796	115,796	115,796	115,796	115,796

This table presents results from logistic regressions of acquisition likelihood on the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index, including controls for valuation waves, described in Appendix A. Macroeconomic variables are averaged over the prior calendar year; all other variables are measured at the end of the prior fiscal year. In all models we include all firm-level control variables from Table 3 and Fama-French 48 industry fixed effects; we cluster standard errors by firm and year. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table B3
Controlling for General Economic Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy uncertainty	-0.678*** (-5.02)	-0.647*** (-3.39)	-0.695*** (-3.88)	-0.660*** (-3.50)				
Macroeconomic uncertainty index	-2.805*** (-2.62)				-2.833*** (-2.78)			
VXO index		-0.005 (-1.26)				-0.008** (-2.21)		
CS sigma past returns			0.873 (0.59)				0.935 (0.56)	
CS sigma past sales growth				-0.440 (-0.47)				-2.134** (-1.97)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	115,796	115,796	115,796	115,796	115,796	115,796	115,796	115,796

This table presents results from logistic regressions of acquisition likelihood on the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index, including controls for general economic uncertainty, described in Appendix A. Macroeconomic variables are averaged over the prior calendar year; all other variables are measured at the end of the prior fiscal year. In all models we include all firm-level control variables from Table 3 and Fama-French 48 industry fixed effects; we cluster standard errors by firm and year. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table B4
Instrumental Variables Analysis

Instrumental variable:	Partisan conflict	Elections no incumbent	Elections 5% margin	All instruments
Policy uncertainty	-0.789*** (-3.07)	-0.929*** (-3.49)	-0.941*** (-3.74)	-0.803*** (-3.23)
Macro controls	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes
N	115,796	115,796	115,796	115,796
F-statistic from first stage regression	41.63	10.93	15.35	22.96

This table presents results from logistic regressions of acquisition likelihood similar to our main tests from Table 3 with the distinction that, here, the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index is instrumented using either the partisan conflict index of [Azzimonti \(2016\)](#) (column 1), or the proportion of assets owned by firms headquartered in states with gubernatorial elections where (i) the incumbent does not run for re-election (column 2) or (ii) the election is won by a margin of 5% or less. In the last column, we use all three instruments simultaneously. The last row shows the F-statistic from the first stage regression corresponding to each specification. In all models we include Fama-French 48 industry fixed effects and cluster standard errors by firm and year. *t*-statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table B5
Acquisition Likelihood and Deregulation

	(1)	(2)	(3)	(4)
Policy uncertainty	-0.677*** (-4.00)	-0.674*** (-3.91)		
Deregulation	0.304*** (2.91)	0.192 (1.64)	0.333*** (3.59)	0.230** (2.10)
Future idiosyncratic volatility decrease		0.105*** (3.11)		0.107*** (3.15)
Deregulation x Future idiosyncratic volatility decrease		0.160** (2.30)		0.147* (1.93)
Δ Idiosyncratic volatility	-5.726*** (-4.27)	-5.767*** (-4.30)	-5.667*** (-3.63)	-5.722*** (-3.67)
Total volatility	-2.366* (-1.79)	-3.020** (-2.22)	-2.793** (-1.98)	-3.457** (-2.41)
Macro & firm controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
N	109,494	109,151	109,494	109,151

This table presents results from logistic regressions modeling the likelihood of announcing a merger in year $t + 1$ as a function of firm and industry characteristics measured at time t . To our baseline specification from Table 3 we add a deregulation indicator variable (“Deregulation” equals one if the firm is in an industry which experienced a deregulation event at time t), an indicator variable which equals one if the firm’s idiosyncratic risk decreases from year t to $t + 1$ (“Future idiosyncratic volatility decrease”) as well as an interaction between the two. We also control for the firm’s change in idiosyncratic risk from $t - 1$ to t (“ Δ Idiosyncratic volatility”). In all models we include Fama-French 48 industry fixed effects and cluster standard errors by firm and year. t -statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table B6
Acquisition Likelihood and Regulatory Uncertainty Spikes

	All Regulation				Financial regulation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy uncertainty	-0.672*** (-3.71)		-0.663*** (-3.59)		-0.678*** (-3.84)		-0.658*** (-3.79)	
Regulatory policy uncertainty spike	-0.032 (-0.35)	-0.113 (-1.02)	-0.142 (-1.39)	-0.231* (-1.95)	-0.035 (-0.30)	-0.097 (-0.59)	-0.275*** (-3.83)	-0.362*** (-3.55)
Future idiosyncratic volatility decrease			0.088** (2.50)	0.087** (2.52)			0.085** (2.53)	0.084** (2.46)
Regulatory PU spike x Future idiosyncratic volatility decrease			0.178*** (4.69)	0.194*** (4.99)			0.319*** (2.88)	0.357*** (2.51)
Δ Idiosyncratic volatility	-5.742*** (-4.26)	-5.663*** (-3.63)	-5.763*** (-4.27)	-5.691*** (-3.65)	-5.827*** (-4.34)	-5.903*** (-3.80)	-5.884*** (-4.49)	-5.967*** (-3.95)
Total volatility	-2.276* (-1.71)	-2.705* (-1.92)	-2.935** (-2.15)	-3.370** (-2.34)	-2.261* (-1.71)	-2.672* (-1.89)	-2.957** (-2.17)	-3.374** (-2.34)
Macro & firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	109,494	109,151	109,494	109,151	109,494	109,151	109,494	109,151

This table presents results from logistic regressions modeling the likelihood of announcing a merger in year $t + 1$ as a function of firm and industry characteristics measured at time t . These tests are identical to the ones from Table B5, the only difference being that here we replace the deregulation indicator variable with a regulatory-uncertainty indicator variable ("Regulatory policy uncertainty spike"). This variable equals one if the [Baker, Bloom, and Davis \(2016\)](#) regulation-specific policy uncertainty index (columns 1-4) or their financial-regulation-specific policy uncertainty index (columns 5-8) experience a "spike" in year t . A spike is defined as the index increasing to more than two standard deviation above its mean and decreasing to below its mean, within year t . In all models we include Fama-French 48 industry fixed effects and cluster standard errors by firm and year. t -statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table B7
Competition and Types of Policy Uncertainty

Panel A: BBD index components											
	News component	Tax component	Gov. spending component	CPI component							
Policy uncertainty	-0.004 (-0.04)	-0.062** (-2.54)	0.085 (1.08)	-0.204 (-1.09)							
Policy uncertainty x TNIC Herfindahl	-0.464*** (-2.96)	-0.011 (-0.34)	-0.303* (-1.68)	0.219 (0.66)							
TNIC Herfindahl	1.948*** (2.66)	-0.143 (-0.86)	1.095 (1.41)	-1.179 (-0.79)							
Macro & firm controls	Yes	Yes	Yes	Yes							
N	73,472	73,472	73,472	73,472							
Panel B: Subcomponents of news component											
	Fiscal policy	Taxes	Gov. spending	Monetary policy	Regulation	Financial regulation	Health care	Entitlement programs	National security	Trade policy	Sovereign debt
Policy uncertainty	-0.015 (-0.23)	-0.047 (-0.73)	0.039 (0.93)	-0.001 (-0.02)	-0.015 (-0.25)	-0.087 (-1.46)	-0.009 (-0.15)	0.075 (1.14)	-0.009 (-0.17)	-0.095 (-1.32)	0.003 (0.19)
Policy uncertainty x TNIC	-0.259*** (-2.94)	-0.251*** (-2.75)	-0.196*** (-3.23)	-0.396** (-2.54)	-0.295*** (-2.59)	-0.130* (-1.75)	-0.224*** (-3.10)	-0.323*** (-3.22)	-0.208 (-1.26)	0.076 (0.48)	-0.031 (-0.90)
TNIC	0.949** (2.38)	0.926** (2.23)	0.633** (2.27)	1.558** (2.27)	1.121** (2.17)	0.342 (1.10)	0.839** (2.48)	1.312*** (2.62)	0.705 (1.00)	-0.506 (-0.79)	-0.070 (-0.53)
Macro & firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	73,472	73,472	73,472	73,472	73,472	73,472	73,472	73,472	73,472	73,472	73,472

This table presents results from logistic regressions of acquisition likelihood on the policy uncertainty, interacted with Herfindahl industry concentration ratios calculated using the [Hoberg and Phillips \(2016\)](#) text-based network industry classifications (TNIC). Policy uncertainty proxies in Panel A are the overall BBD policy uncertainty index and its four components. In Panel B we measure policy uncertainty using the subcomponents of the index's news component. A list of the search terms used to create these subcomponents can be found at: http://www.policyuncertainty.com/categorical_terms.html. All specifications include simultaneous firm-level controls and macroeconomic controls for as in Table 3. Detailed variable definitions are in Appendix A. In all models we include Fama-French 48 industry fixed effects and cluster standard errors by firm and year. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table B8
Policy Uncertainty and Private Target Acquisition Likelihood

	News component	Tax component	Gov. spending component	CPI component
Policy uncertainty	-0.749*** (-3.05)	-0.110* (-1.93)	-0.349** (-2.36)	-0.811*** (-3.60)
Investment opportunities (First principal component)	-0.030** (-2.53)	-0.004 (-0.29)	-0.008 (-0.50)	-0.010 (-0.84)
Industry economic shock	0.059*** (3.03)	0.029 (1.27)	0.045** (2.07)	0.043** (2.03)
Rate spread	0.174*** (4.28)	0.085*** (2.71)	0.112*** (3.31)	0.066** (2.42)
Shiller's PE ratio	0.028*** (4.21)	0.016 (1.57)	0.015* (1.86)	0.010 (1.26)
Industry median Q	0.138 (1.35)	0.276** (2.20)	0.246** (2.07)	0.219* (1.81)
Industry median past returns	0.236*** (3.31)	0.260*** (3.56)	0.229*** (2.87)	0.278*** (3.43)
Industry sigma past returns	-0.048*** (-2.66)	-0.040* (-1.85)	-0.039* (-1.91)	-0.035 (-1.60)
Macroeconomic uncertainty (First principal component)	-0.051*** (-3.88)	-0.032 (-1.56)	-0.037* (-1.82)	-0.023 (-1.13)
Log total assets	0.108*** (7.23)	0.106*** (7.20)	0.108*** (7.29)	0.108*** (7.29)
ROA	0.908*** (9.01)	0.895*** (9.31)	0.912*** (9.36)	0.917*** (9.52)
Sales growth	0.337*** (13.00)	0.337*** (12.74)	0.337*** (12.77)	0.341*** (13.07)
Book leverage	-0.541*** (-5.19)	-0.553*** (-5.13)	-0.555*** (-5.18)	-0.558*** (-5.18)
Cash to total assets	0.442*** (4.90)	0.449*** (5.17)	0.427*** (4.77)	0.438*** (4.96)
Market-to-book	0.019*** (4.37)	0.018*** (4.24)	0.019*** (4.43)	0.019*** (4.36)
Past returns	0.109*** (6.64)	0.108*** (6.87)	0.109*** (7.04)	0.105*** (6.62)
Firm-level volatility	-2.476** (-2.00)	-2.686** (-2.18)	-2.304* (-1.91)	-2.293** (-1.97)
Time trend	0.018*** (4.03)	0.036** (2.33)	0.008 (1.31)	0.013** (2.11)
N	115,796	115,796	115,796	115,796

This table presents results from logistic regressions modeling the likelihood of announcing an acquisition of a private target in year $t + 1$ as a function of firm and industry characteristics measured at time t . Each column corresponds to a different subcomponent of the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index. All other control variables are identical to our baseline specification from Table 3. In all models we include Fama-French 48 industry fixed effects and cluster standard errors by firm and year. t -statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table B9
Policy Uncertainty and the Method of Payment

	Stock deal: 100% stock			Stock deal: >50% stock		
Policy uncertainty	0.160 (0.66)	0.571** (2.26)	0.594** (2.52)	0.241 (1.33)	0.499*** (3.60)	0.386** (2.30)
Policy uncertainty x M/B		-0.084** (-2.18)			-0.049* (-1.69)	
M/B		0.402** (2.15)			0.215 (1.44)	
Policy uncertainty x Past returns			-0.088*** (-2.72)			-0.032 (-0.96)
Past returns			0.400*** (2.61)			0.133 (0.79)
Macro & firm controls	Yes	Yes	Yes	Yes	Yes	Yes
N	115,796	115,796	115,796	115,796	115,796	115,796

This table presents results from the second stage of two-stage Heckman probit models which investigate the effect of policy uncertainty on the likelihood of acquiring a target using stock financing. The dependent variable in the second stage equals one if the financing for the deal is 100% stock (columns 1-3) or at least 50% stock (columns 4-6). As proxies for acquirer overvaluation, we use the firm's market-to-book equity ratio (columns 2 and 4) and its cumulative returns in the past 12 months (columns 3 and 6). Both of these proxies are converted to decile ranks (values 0 through 9) and are interacted with the [Baker, Bloom, and Davis \(2016\)](#) policy uncertainty index. All controls from our baseline specification are present in the second stage probit, but are omitted from the table for simplicity. The first stage (not shown) predicts the likelihood of announcing an acquisition, as in first model in [Table 3](#) with the addition of a proxy for hypothetical mechanical mutual funds outflows to the firm, calculated following [Edmans, Goldstein, and Jiang \(2012\)](#). In all models we include Fama-French 48 industry fixed effects and cluster standard errors by firm and year. *t*-statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.