Product Price Risk and Liquidity Management: Evidence from the Electricity Industry

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Abstract

Product price risk is a potentially important factor for firms' liquidity management. A natural place to evaluate the impact of this risk on liquidity management is the electricity industry, since producing firms face substantial price volatility in wholesale markets. Empirically, higher volatility of electricity prices leads to an increase in cash holdings, and this effect is robust to instrumenting for price risk using weather volatility. Cash increases more with price risk in firms using inflexible production technologies and those that cannot easily hedge electricity prices, indicating that operating flexibility and hedging are substitutes for liquidity management.

JEL classification: G30, G32

Key words: Electricity price volatility, cash holdings, weather volatility, operating flexibility, hedging

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1. Introduction

One of the most important decisions a financial manager must make concerns the liquidity of his balance sheet, in particular, the amount of cash that his firm should hold. The most prominent explanation of corporate liquidity decisions was originally proposed by Keynes (1936), and is known as the precautionary theory of savings. This theory posits that firms hold cash as a hedge against the possibility that they will subsequently face financial constraints that distort their investment decisions.

In this paper, we analyze the impact of a particular source of risk on firms' liquidity management. We focus on the risk that product price movements can lead to cash flow shortfalls in the electricity-generating industry.¹ In many parts of the world, electricity-producing firms sell at least part of their production in volatile wholesale markets. High-frequency price data from 40 deregulated electricity markets around the globe enable us to estimate the distribution of prices and hence the product price risk for the 213 firms that operate in these markets.² Our empirical analysis evaluates the extent that these firms' choices of quarterly cash holdings depend on electricity price volatility. This approach allows for precise identification of both the product price risk each firm faces and the firms' management of this risk.

A number of studies have documented that, consistent with the precautionary savings argument, firms with more volatile cash flows tend to hold more cash.³ Measuring cash flow volatility at the firm level is challenging for a number of reasons, including a lack of high-frequency cash flow data, the backward-looking nature of the measure, potential survivorship bias due to the requirement of data about a firm's cash flow history, and the effect of a firm's financial policies (including liquidity management) on its cash flows.

Analyzing cash flow uncertainty stemming from product price in the electricity industry has a number of advantages relative to prior studies that focus on the volatility of firms' overall cash flows. First, investigating product price characteristics allows us to identify the source of overall cash flow variations.

¹ Theoretically, the idea that uncertainty about product prices affects firms dates back to Sandmo (1971).

² These markets are in located in 32 countries, and represent virtually all markets that operate a day-ahead market for electricity and have hourly pricing. Section 2.1 provides an overview on the markets and the criteria for their inclusion. ³ The empirical literature examining this hypothesis began with Opler, Pinkowitz, Stulz, and Williamson (1999). See Almeida, Campello, Cunha, and Weisbach (2014) for a survey.

Second, the high-frequency electricity price data enables us to calculate price volatility within a firm's fiscal year. In contrast to risk measures based on firms' reported cash flows, this setting makes the inclusion of firm-fixed effects straightforward. Third, electricity is a completely homogenous good that does not vary in quality, which makes its price comparable across regions and time. Fourth, electricity-producing firms sell only one product, i.e., electricity. Fifth, electricity wholesale prices can fluctuate substantially, for instance because electricity demand tends to be price inelastic and storing electricity is prohibitively expensive. Sixth, a large source of this variation in wholesale electricity prices occurs because of an exogenous factor affecting the demand for electricity, the weather. Fluctuations in weather therefore provide a valid instrument for price volatility. For these reasons, our analysis of electricity price volatility allows us to identify the way in which firms' liquidity management decisions depend on product price risk and, more generally, uncertainty about cash flows.

Our estimates suggest that firms do increase their cash holdings in response to higher volatility of wholesale prices. Based on models which only exploit time series variation of a firm's price risk over time, a one-standard deviation increase of the product price volatility leads to an increase in cash holdings (normalized by assets) of 0.4 percentage-points, which corresponds to a seven percent increase relative to the mean cash to assets ratio of .05. To isolate the channel through which price risk affects liquidity decisions, we instrument for electricity price volatility using the volatility of daily temperatures within an electricity market. First-stage IV estimation results confirm the relevance of our instrument, with an F-stat of about 40. The results from both reduced form and second-stage IV results imply that incremental product price risk leads firms to hold more cash.

There are several institutional features of the wholesale electricity market that could potentially affect the interpretation of our findings. First, while we have presumed that firms are price takers, at least some firms do have considerable market power (see, for instance, Borenstein, Bushnell, and Wolak, 2002). Their market power could allow them to influence the auction-based market prices via their bidding behavior. We repeat our main tests using only firms that have a low market share in terms of generation capacity and thus limited influence on the price-setting. Furthermore, those smaller firms tend to be less

strategically sophisticated (Hortacsu et al., 2017). In addition, we also analyze demand volatility instead of price volatility since demand volatility is unaffected by supply-side factors such as firms' bidding behavior. The results from these alternative specifications are similar to those discussed above.

In addition, firms do usually not sell all their electricity on the day-ahead market, but also use longterm bilateral contracts in many markets. To evaluate how this affects our results, we first exclude all markets for which the day-ahead market accounts for less than one-third, half, or two-thirds of the electricity consumption. Second, we use data on electricity transactions in the U.S. from FERC's EQR database to calculate a measure of realized price volatility. This measure is defined as the standard deviation of the actual prices a firm receives for its electricity so explicitly considers day-ahead market transactions and sales based on bilateral contracts. These alternative approaches again leads to similar results.

In addition, we directly analyze whether hedging opportunities can mitigate the impact of price volatility on firms' liquidity management. Pre-selling part of their electricity production via futures, forwards, or bilateral contracts can protect firms from volatile wholesale prices, at least in the short run. In the electricity industry, firms' abilities to hedge in derivative markets varies substantially across regions because of differences in the availability and liquidity of hedging instruments across markets. These differences allow us to evaluate the extent to which hedging and cash holdings are substitutes. We construct three measures of a firm's ability to hedge product price risk. The first is based on a survey among European firms conducted in 2008 for the European Commission. In this survey, firms were asked to rate their ability to trade forward in a particular electricity market. The second is the fraction of electricity transactions in a particular market that were based on fixed prices.⁴ The third measure uses the same electricity transaction data, but aggregates them on the firm instead of the market level.

Using each of these measures, our estimates suggest that the ability to hedge through derivative markets does act as a substitute for cash holdings. Firms that can easily hedge the electricity price adjust their cash holdings to changes in volatility less than otherwise identical firms without such hedging

⁴ FERC's EQR database enables us to differentiate sales that use market rates versus sales that use pre-determined fixed rates (e.g., bilateral contracts).

opportunities. Since it is usually cheaper to hedge through the derivatives market than by holding cash, firms appear to rely on derivatives when markets for them exist and are liquid. This result highlights the way in which derivative markets are substitutes to liquidity management, and suggests that a benefit of having liquid derivative markets is that they allow firms to hold less cash on their balance sheets.

Electric utilities use different technologies to generate electricity. Some of these technologies such as gas-fired power plants are highly flexible and have low fixed cost ("flexible generators"). Other technologies such as coal or nuclear are less flexible and they have much higher fixed cost ("baseload generators"). Thus, electricity-producing firms are likely heterogeneous with regards to their exposure to wholesale market volatility. Flexible generators are likely to bid near their marginal cost (see Puller, 2007 and Hortacsu and Puller, 2008). Because flexible generators do not have to sell if the wholesale market price is lower than their bid, their exposure to the price volatility is limited. Baseload producers with high fixed costs, however, often bid near zero in order to ensure that they can sell their electricity and therefore receive whatever the market price happens to be. For this reason, baseload producers are particularly vulnerable to price risk, even though there is at least some cost pass-through in electricity markets.⁵ Low-flexibility firms are therefore the ones for which electricity price volatility should matter the most, and operating flexibility is likely to affect the way in which individual firms manage risk.⁶

Using data on about approximately 50,000 individual power plants, we estimate the way in which firms' liquidity adjustments depend on characteristics of their method of production. We find that product price risk has little effect on liquidity management for firms using relatively flexible gas-fired or oil-fired plants. Consistent with the notion that firms with inflexible production like coal have greater demand for hedging price risk, our estimates indicate that cash holdings increase substantially with product price

⁵ For instance, Fabra and Reguant (2014) show that about 80 percent of CO2 emission cost are passed through to electricity prices. Such pass-through mechanism can partly reduce the price risk for electricity producers with flexible, price-setting generation. Baseload producers, however, still face price risk for two reasons. First, their profits decrease if the price-setting technology (e.g., gas) in the merit order becomes less expensive, independently of any pass-through. Second, a less expensive technology can become price-setting in the merit order if electricity demand decreases, which reduces the profit for baseload producers even if there is a cost pass-through.

⁶ The idea that flexibility in production affects how firms react to price risk goes back to theoretical work by Turnovsky (1973) and Epstein (1978).

volatility for these firms. For the bottom half of our sample firms ranked in terms of operating flexibility, a one standard deviation increase in price volatility leads to a ten percent relative increase in cash holdings, compared to four percent for the top half (the latter being statistically not different from zero).

There are several potential concerns with this operating flexibility analysis. First, wind and solar power plants are special forms of electricity generation because they cannot be actively dispatched, and are often subsidized (e.g., Joskow, 2019, p. 4). For these reasons, we exclude wind and solar plants when calculating our main measure for operating flexibility. We also find similar results if we exclude hydro plants, pump storage, or nuclear plants. Second, flexible and inflexible generation technologies can differ in aspects other than flexibility. For instance, inflexible production assets like coal or nuclear plants tend to have a higher environmental liability exposure than flexible plants. However, controlling for effects of environmental policy stringency based on an OECD index indicates that such differences in liability exposure are unlikely to drive our results. Third, we address concerns that production assets are endogenously determined by using the average flexibility of other firms in the same market and by using weather volatility instead of electricity price volatility. All these tests lead to similar results as our main specification.

Our analysis extends the literature in a number of ways. First, we measure the extent to which energy utilities adjust their cash holdings in response to wholesale price risk. By isolating one particular source of cash flow risk and documenting firms' responses to this risk, we provide a particularly clean test on how product price risk affects corporate liquidity management and document that firms adjust their cash holdings in response to product price risk. This finding adds to the growing literature on the determinants of corporate liquidity management (e.g., Almeida, Campello, and Weisbach, 2004, Bates, Kahle and Stulz, 2009, Lins, Servaes, and Tufano, 2010, Graham and Leary, 2018) and the literature on product markets and firms' financial decision making (e.g., Haushalter, Klasa, and Maxwell, 2007, Hoberg and Phillips, 2010, Hoberg, Phillips, and Prabhala, 2014). Furthermore, our focus on price volatility also contributes to the literature on price flexibility. Bils and Klenow (2004), for instance, document the general importance of

sticky prices, Gorodnichenko and Weber (2016) show that price stickiness can affect stock returns, and D'Acunto et al., 2018 find that price flexibility is an important determinant of financial leverage.

Second, our detailed asset-level data on the methods of producing electricity used by different firms enables us to measure the way in which firms' reactions to price risk depends on the flexibility of their production process. Our analysis therefore complements the prior literature on operating flexibility and firm outcomes. Mauer and Triantis (1994), for instance, analyze theoretically how operating adjustment costs affect financing decisions. Empirical evidence in this context is provided by MacKay (2003) and Reinartz and Schmid (2016), who study the way in which operating flexibility affects financial leverage.

Third, this paper provides some evidence that firms' cash holdings and derivative usage are substitutes for one another. This finding complements Disatnik et al. (2014), who document that there is a negative relation between the "cash flow hedging" of an individual firm and its cash holdings. It also adds to prior literature on the financial consequences of hedging through derivatives (e.g., Perez-Gonzalez and Yun, 2013) and the interaction between operational and financial hedging (e.g., Hoberg and Moon, 2017; Giambona, Graham, Harvey, and Bodnar, 2018). Prior literature which investigates the impact of different forms of operating flexibility on firms' cash holdings includes Gamba and Triantis (2013), Ghaly, Dang, and Stathopoulos (2017), or Kouvelis, Wu, and Xiao (2019). We also contribute to the literature on the choice between cash and lines of credit. Related to theoretical predictions of Acharya (2013), we find that firms facing higher price risk prefer holding cash relative to lines of credit.

Fourth, this study adds to the literature on how firms adapt to deregulation. Fabrizio, Rose and Wolfram (2007), for instance, analyze how efficiency of energy utilities is affected by regulatory changes, and Ovtchinnikov (2009) investigates capital structure decisions after deregulation for multiple industries. An important step of the deregulation process is the establishment of wholesale markets for electricity, and our estimates imply that the introduction of these markets leads to an increase in cash holdings of about 1.2 percentage-points, which corresponds to a 20 percent relative increase. Because holding cash is costly for firms, this result suggests that a hidden cost of deregulation is that it increases the price risk faced by firms.

2. Wholesale Price Fluctuations and Liquidity Management

2.1. The Wholesale Market for Electricity

Competitive wholesale markets for electricity exist in many countries. In these markets, the prices for electricity adjust to reflect the supply and demand at a particular point in time. Non-commercial consumers typically pay a pre-arranged rate to their retail company. These retail companies, however, typically purchase electricity they sell to consumers from the wholesale market at whatever the price happens to be. In this paper, we focus on the electricity-generating firms which are the supplies of electricity on the wholesale markets.

Wholesale markets for electricity usually have a day-ahead market (DAM) in which market participants buy and sell electricity for delivery on the following day. Thus, this market is essentially a short-term futures market. The DAM price for electricity is formed independently for each hour of the next day in an auction between buyers and sellers. Some wholesale markets also offer real-time markets in which electricity for delivery on the same day is traded. Furthermore, generators can use bilateral contracts to sell electricity (often with pre-determined, fixed prices). In this paper, we will focus on DAM prices because real-time markets tend to be much smaller and less liquid.⁷ Later, we will explore the role of bilateral contracts and hedging opportunities in general for firms' liquidity management (see Section 5.1).

Wholesale electricity markets have developed in different regions of the world, with slightly different structures and regulations. In the U.S., the Federal Energy Regulatory Commission (FERC) order 2000, which was issued in February 2000, set the starting point for the creation of regional wholesale markets for electricity. Independent system operators (ISOs) and regional transmission organizations (RTOs) then formed market regions with day-ahead wholesale markets for electricity. Currently there are seven organized markets in the U.S. These are ISO New England, New York ISO, PJM, Midwest ISO, Southwest Power Pool, ERCOT, and California ISO. While some of those markets focus (approximately) on a single state (e.g., ERCOT covers most of Texas), others serve regions with multiple states (e.g., PJM

⁷ Longstaff and Wang (2004) provide a detailed discussion of the electricity market structure for the PJM market.

covers all or part of 13 states). Regions outside these markets do not have competitive markets for electricity and electricity is supplied by rate-regulated utilities.⁸

In Europe, the process of deregulating electricity markets and introducing wholesale markets for electricity was started in 1996 by the European Union Directive 96/92/EC. By the early 2000s, most E.U. markets were deregulated. Most wholesale markets in Europe cover one country, but Nordpool, the largest electricity market in Europe, is an important exception and covers several northern European countries. In Asia and Oceania, the deregulation process varied substantially across countries. Australia, for example, was an early adopter and started introducing wholesale markets in the mid-1990s. It now has multiple markets, which generally cover single states. There are no markets for which we are able to obtain data during our sample period in South America and Africa.

We collect hourly electricity prices for 40 power markets located in 32 countries. We do not consider markets which were active for less than five years during our sample period, markets without dayahead trading, and markets without hourly pricing.⁹ While the basic structure of electricity markets is similar across the globe, the markets differ in a number of ways. Because it is difficult to control for all cross-regional differences econometrically, we focus on time-series variation of electricity price volatility within a market in most of our tests. Figure 1 illustrates the wholesale markets in our sample as well as their average electricity price volatility. These regions cover a large portion of the developed economic world.

2.2. Hypotheses

The volatility of electricity prices in those wholesale markets creates cash flow risk for electricity producers. Almeida, Campello, Cunha, and Weisbach (2014) formally model a problem similar to the one faced by electricity producers. In this model, the firm faces an uncertain cash flow requirement to continue

⁸ Even some states located in regions with wholesale markets for electricity still maintain traditional rate regulation. (e.g., most states in the Midwest ISO). See, for instance, Cicala (2017) for more details.

⁹ For this reason, we do not include the Southwest Power Pool (starting in 2013), IBEX in Bulgaria (2014), EPIAS in Turkey (2015), and CROPEX in Croatia (2016). Furthermore, we ignore markets which do not feature a typical dayahead market with hourly pricing (WESM, Philippines). Hourly electricity prices could not be obtained for the markets in Argentina, Brazil, Colombia, and Slovenia.

a valuable investment, leading the firm to hold cash in anticipation of the potential cash flow shock. A clear implication of this model is that when the magnitude of a potential cash flow shock increases, a firm should hold more cash. Thus, our first hypothesis is:

H1: Higher electricity price volatility leads to higher cash holdings

However, it is important to note that not all electricity-producing firms are likely to be equally affected by volatility in wholesale prices for electricity. If firms can use bilateral contracts or other instruments like forwards or futures to pre-sell their electricity, their exposure to the volatility on the day-ahead market is limited.¹⁰ Thus, hedging opportunities can mitigate the impact of price volatility on firms' liquidity management. In this sense, the use of hedging instruments can substitute for cash holdings because they transfer cash flows to the states of the world where they are most valuable (Froot, Scharfstein and Stein, 1993). Because holding cash is costly for firms due to tax reasons, financial hedging is less expensive for firms (Almeida et al., 2014).¹¹ Thus, firms are likely to prefer hedging through derivative markets if such contracts are readily available. Using heterogeneity with regard to the availability of hedging opportunities will enable us to test our second hypothesis:

H2: The impact of electricity price volatility on cash holdings is concentrated in firms with little hedging opportunities

In addition, the technology used to generate the electricity is likely to affect the impact of wholesale price volatility on liquidity management. Flexible producers with low fixed cost can bid prices near their marginal cost, which at least partially reduces their exposure to (low) wholesale market prices. By contrast, baseload producers with high fixed cost typically bid near zero to ensure that they can sell their electricity. These firms with low operating flexibility are the ones that are most exposed to (low) wholesale market prices. Using detailed asset-level data on firms' power plants will enable us to test our third hypothesis:

¹⁰ Although hedging limits firms' exposure to spot prices in the short-run, medium and long-term effects are less clear because higher spot price uncertainty also creates higher uncertainty about the price for which contracts can be entered in the future.

¹¹ Faulkender, Hankins, and Petersen (2019) show that some firms accumulate cash in foreign subsidiaries for tax reasons. This effect is likely less relevant for our study firms because foreign subsidiaries are less common in the energy utility sector.

H3: The impact of electricity price volatility on cash holdings is concentrated in firms with low operating flexibility ("baseload producers")

3. Data Description

3.1. Sample of Electricity Producing Utilities

Our sample consists of publicly-traded utilities in the 2000 to 2016 period. For all countries except the U.S. and Canada, we start by combining lists of active and inactive utility companies from *Thomson Reuters*. We clean this sample by eliminating all firms without a primary security classified as equity, and obtain data on their power plants for this sample form the *Platts* WEPP database (see Section 3.3). For the U.S. and Canada, we rely on the *S&P Market Intelligence* database. This database covers all utilities from those two countries, including detailed data on their balance sheets and power plants. Because we rely on data on financial statements, we drop all firms that are not public stock corporations.

After combining the samples, we want to consider only companies that focus on the generation of electricity. To ensure that other companies are not included, we rely on firms' SIC and ICB codes, the business description obtained from *Capital IQ*, and additionally conduct manual research on the companies' business lines. We also drop utilities with less than 100 megawatts of production capacity because electricity generation is likely not their main business.¹² We then eliminate utilities for which solar or wind plants account for more than half of their overall production capacity because those plants are special in several dimensions. Among others, they are often subsidized and have zero marginal production cost (see Joskow, 2019, for more details about intermittent renewable generation).¹³ As a last step, we remove firms that do not operate in regions with competitive wholesale markets for electricity from our main sample (we

¹² The average capacity of a single gas-fired plant in the U.S. is 120 MW. The corresponding figure for a single coalfired plant is 340 MW.

¹³ Internet Appendix 1.5 shows that our main results are not sensitive to the choice of this threshold. Furthermore, wind and solar plants could influence our results because they can affect electricity prices due to the merit order effect. Because wind and solar have zero marginal production cost, they are first used to satisfy electricity demand. Thus, they can shift the merit order and reduce the electricity price because a cheaper production technology becomes pricesetting (e.g., lignite instead of hard coal). However, we do not expect them to have a major impact during our sample period because they account on average for only five percent (median: two percent) of a market's production capacity.

add those firms back for our deregulation tests in Section 4.5). We end up with a sample of 213 unique electricity-generating that operate a total of about 50,000 unique power plants.

3.2. Wholesale Electricity Price Data

To measure the degree of electricity price volatility, we use hourly data on electricity prices in each market. These data are available for 40 regional markets from 32 countries. We obtain the price data from the websites of power exchanges, direct contact with exchanges, or from *Thomson Reuters*. To make the prices comparable across countries, all prices are converted into U.S. dollars using daily exchange rates.

To illustrate that there are considerable differences with regard to price fluctuations across markets, we present time series plots of electricity price times for in three selected markets in Figure 2: the German market, Nordpool, and the state of New York. The full time series for all three markets is shown in the first subfigure. In the following subfigures, we show an exemplary year, month, and week for those markets. The German market consistently has higher price volatility than the New York market, which in turn has higher volatility than the Nordpool market. This figure also illustrates that there is considerable variation of the electricity price within a year, month, and day. For example, the price for electricity in the German market fluctuated between around minus 50 US\$ per MWh and 100 US\$ per MWh in January 2012. The fact that wholesale market buyers had to pay between 50 US\$ per MWh and nearly 100 US\$ per MWh on January 15 illustrates the intra-day fluctuations of the electricity price. Part of these price variations are related to (predictable) seasonal factors, which is another reason why we mainly focus on changes of electricity price volatility over time within a particular market in most of our empirical analyses. Using this approach, we ensure that our results are not affected by time-constant seasonal factors in a market.

Since our goal is to evaluate the way in which product price risk affects firms' liquidity management, we calculate different measures of the wholesale price fluctuations. To do so, we first calculate a measure we refer to as *VOLATILITY*. This measure equals the standard deviation of hourly electricity prices in the firm's electricity market during its fiscal quarter, normalized by the average

electricity price in that market.¹⁴ If a firm is active in more than one wholesale electricity market, *VOLATILITY* is the capacity-weighted average of the normalized standard deviations of electricity prices in those markets. For most of the analysis, we focus on the natural logarithm of *VOLATILITY* as our main measure of product price risk. To ensure that this measure is comparable over time, we only calculate it if at least 2,150 hourly electricity price observations are available for a firm-quarter.

Besides our main measure of product price risk, we calculate several alternative volatility measures. First, we calculate the standard deviation of hourly electricity prices without scaling it by the average electricity price in that market. Second, we construct an alternative definition of volatility based on the standard deviation of hourly electricity price changes. Third, we define volatility as the standard deviation of hourly changes in electricity prices, normalized by a market's average electricity price level.

3.3. Power Plant Data

Our measures for operating flexibility are based on the generation technologies of the sample firms' power plants. Data on the production technologies for single power plants are obtained from the annual versions of the *Platts World Electric Power Plant* database for all firms outside the U.S. and Canada. This comprehensive database includes information on single power plant units, including their production technologies, capacities, geographic locations, start dates of commercial operation, and their owners/operators.¹⁵ We obtain this database for all years between 2000 and 2016 and manually match each power plant in this database to the energy utilities sample. About 50% of the plants match to our sample firms; the remainder are, for instance, owned by large utilities that are not publicly listed and are excluded from our sample for this reason. For U.S. and Canadian firms, data on power plants comes from the *S&P*

¹⁴ We use hourly prices to calculate volatility because daily prices, which are simply aggregations of hourly prices, are less precise than hourly prices for our purpose. For example, assume a daily price of 100 USD. If the price was 100 USD for all hourly contracts, it would have been optimal to run coal-fired plants in all hours. However, if the price was zero for 12 hours and 200 for the other 12 hours, switching on and off the plant would have been the optimal strategy. These two cases cannot be distinguished when using daily prices.

¹⁵ A detailed description of the database is provided by *Platts' Data Base Description and Research Methodology* (www.platts.com/IM.Platts.Content/downloads/udi/wepp/descmeth.pdf).

Market Intelligence database. This database includes the history of ownership changes, which allows us to identify the power plants our sample firms owned in each year. Based on this asset-level data we will construct measures for firms' operating flexibility in Section 5.2.

3.4. Hedging Data

Because firms do typically not sell all their electricity on the day-ahead market, the hedgability of electricity prices plays an important role. We use two datasets to measure how easily firms can hedge the electricity price. The first is based on a survey among European firms which was conducted in early 2008 for the European Commission.¹⁶ This survey provides a comprehensive picture of the hedgability of electricity prices in European markets because it is not limited to hedging instruments that are traded on exchanges (i.e., mainly futures in the context of electricity), but also covers OTC contracts.

The second dataset is the Electric Quarterly Reports (EQR) database of the FERC, which contains almost all electricity transactions of U.S. utilities.¹⁷ This database does not only contain the price for each transaction, but also indicates whether a market-based rate or a fixed rate was used. Since 2014 is the first full year for which firms have to disclose the type of rate used in a particular transaction, we use this year as starting point for our tests which are based on EQR data. Because utilities located in the ERCOT market region are exempt from this regulation, we exclude them from all tests using EQR data. After downloading quarterly EQR data from 2014 from the FERC website and processing more than 100 million individual

¹⁶ Moffatt Associates Partnership: "Review and Analysis of EU wholesale energy markets", prepared for the European Commission DG TREN.

¹⁷ According to FERC, "[t]he EQR is the reporting mechanism FERC uses for public utilities to fulfill their responsibility under section 205(c) of the Federal Power Act (FPA) [...] The EQR contains Seller-provided data summarizing contractual terms and conditions in agreements for all jurisdictional services, including cost-based sales, market-based rate sales, and transmission service, as well as transaction information for short-term and long-term market-based power sales and cost-based power sales."

transactions, we construct measures for realized price volatility (see Section 4.4) and the use of fixed-price bilateral contracts (see Section 5.1).

3.5. Financial Variables

Financial variables come from *Market Intelligence* (U.S./Canada) or *Worldscope* (all other countries). Our measure of cash holdings is calculated as the total cash holdings of the firm at the fiscal quarter end normalized by the book value of assets at the same time period. The main control variables included are size (measured as the natural logarithm of total assets), cash flow (earnings before interest, taxes, depreciation, and amortization scaled by total assets), leverage (total debt divided by the sum of total debt and book value of equity), and GDP (the natural logarithm of the GDP per capita).¹⁸ In additional tests, we also control for several other possible determinants of cash holdings, such the market-to-book ratio (market capitalization divided by the book value of equity), capital expenditures (scaled by total assets), dividend payments (a dummy variable which equals one if a divided is paid), and the inflation rate. To restrict the impact of outliers, all variables are winsorized at the 1% and 99% levels.

3.6. Descriptive Statistics

Panel A of Table 1 shows the descriptive statistics for our sample firms, averaged over all firmquarters. On average, energy utilities have cash holdings equal to five percent of their total assets. Furthermore, there is considerable variation in the cash ratio with an inter-quartile range of six percentage points. The average value of *VOLATILITY* is 0.46, with a standard deviation of 0.56. The average value of *FLEXIBILITY* is 0.39, with a standard deviation of 0.27. The average firm in our sample has total assets of around 24 billion USD (median: 13 billion USD). Panel B of Table 1 presents a correlation matrix for the different volatility measures, and indicates that all measures are highly correlated.

¹⁸ All financial variables are measured in U.S. dollars. Both the measure of cash holdings and the control variables have become standard in the literature on cash holdings since Opler, Pinkowitz, Stulz and Williamson (1999).

4. Estimating the Impact of Product Price Risk on Liquidity

4.1. Empirical Specification

To measure the impact of product price risk on liquidity management decisions of electricity producing firms, we estimate the extent to which their cash holdings are affected by the volatility of electricity wholesale prices.¹⁹ In our equations predicting an energy utility's cash holdings, we use measures of electricity price volatility a firm faces in a particular quarter as our primary independent variable.

Because wholesale electricity market prices contain variation both across and within years, our data are organized at the firm-quarter level. To account for the fact that electricity price seasonality can differ between countries, we include quarter times country fixed-effects in our main specification (in addition to year-fixed effects). As discussed before, electricity markets differ along dimensions which are difficult to control for. For this reason, and because there is likely to be unobserved heterogeneity between firms, our main specification includes firm-fixed effects. Thus, it exploits variation of electricity price volatility over time within firms. In addition, we include the firm's log (assets), its cash flow (normalized by assets), its leverage (total debt scaled by total debt plus book value of equity), and the log of the annual GDP per capital (in 2010 USD) in each equation. In our main specification, we use contemporaneous firm-level control variables because not all firms report financial data for all quarters (lagged firm-level controls are used as a robustness test). For GDP, we use the lagged annual value because the contemporaneous value would be forward looking for the first, second, and third quarter. The reported t-statistics are based on robust Huber/White standard errors (White, 1980), clustered by countries. For tests that only focus on the U.S., standard errors are clustered by markets. We present alternative ways to account for seasonality and clustering in the Internet Appendix.

4.2. Estimates of the Impact of Product Price Volatility on Cash Holdings

¹⁹ The cash holdings variable we rely on includes holdings of a number of securities, some of which are risky (see Duchin, Gilbert, Harford and Hrdlicka (2017)),

We present estimates of the impact of product price volatility on cash holdings in Table 2. We first present estimates that include country-fixed effects but no firm-fixed effects in Column (1). In Column (2), we add country times quarter fixed effects to allow for a country-specific seasonality in the electricity price. These estimates suggest that, consistent with theoretical predictions, higher wholesale price volatility is associated with higher cash holdings. The estimates imply that a one-standard deviation increase in volatility leads to a 0.5 percentage-point increase of the cash ratio. Since the average cash ratio in our sample is 0.05, this increase represents approximately a 10 percent change. In Columns (3) and (4), we include firm-fixed effects. The inclusion of firm-fixed effects lowers the predicted impact of a one standard deviation increase in volatility to a 0.4 percentage-point increase in cash holdings, which represents a seven percent change. These calculations indicate that when product price risk is higher, firms tend to increase their cash holdings, presumably as a way of managing their liquidity.²⁰

4.3. Identifying the Equation Using Weather Uncertainty as an Instrument for Price Volatility

The estimates in Columns (3) and (4) of Table 2 include firm-fixed effects and thus are based on variation in wholesale price volatility over time rather than across firms. There are at least two reasons why volatility could potentially be correlated with the residual in the equations reported in Table 2. First, in some circumstances, firms are not price takers and do have an impact on the prices they pay. Second, it is conceivable that electricity price volatility in a market could be correlated with other time-variant country factors, such as economic growth expectations. If these factors also affect firms' liquidity management, they could lead to a nonzero correlation between volatility and the residuals in the estimated equations.

To address such concerns and to identify the impact of product price risk on firms' liquidity policies more cleanly, we exploit the fact that electricity prices are heavily influenced by an exogenous factor – the weather (Perez-Gonzalez and Yun, 2013). Electricity demand varies considerably over time, with weather being a major factor influencing demand. In addition, electricity is non-storable in an economically meaningful way and its demand tends to be price inelastic. As a consequence, the price of electricity

²⁰ Various robustness tests and a graphical illustration of the first-order importance of product price risk for cash holdings can be found in the Internet Appendix.

fluctuates considerably over time because of demand volatility, and one important driver of demand volatility is the weather. Thus, higher fluctuations in temperatures increase the volatility of electricity demand, which in turn leads to a higher volatility of electricity prices.

Since weather is out of any firm's control and affects the volatility of electricity prices, weather provides a valid instrument for price volatility. We construct an instrument for electricity price volatility using the volatility of daily temperatures in a power market and quarter. Similar to our main analyses, we focus on time-series variation in the volatilities of temperatures and electricity prices within firms over time because there are likely to be many unobservable factors that influence both temperatures and prices in the cross section. We obtain data on daily temperatures from the Global Historical Climatology Network (see Menne et al., 2012, for a detailed description of this dataset). These daily temperatures are measured on the weather-station level, so we match all weather stations to electricity markets.²¹ We calculate the daily average temperature in a power market as the mean over all weather stations in that market and *WEATHER VOLATILITY* as the standard deviation of daily temperatures during a firm's fiscal quarter.²²

We start with a reduced form estimation in Column (1) of Table 3. This specification is identical to Column (4) of Table 2, but we replace the natural logarithm of electricity price volatility with the natural logarithm of the weather volatility. We find clear evidence that this variable has a positive impact on firms' cash holdings. A one-standard deviation increase in weather volatility leads to a 0.5 percentage-point increase of the cash ratio, which corresponds to a ten percent relative increase. This magnitude is nearly identical to our main specification in Table 2.

To evaluate further whether the volatility of the weather is related to electricity price volatility, we estimate a first stage regression, in which we predict price volatility as a function of weather volatility. Estimates of this equation, reported in Column (2) of Table 3, indicate that weather volatility clearly predicts

²¹ More precisely, we only use data from weather stations for which we have information on the daily temperatures for all sample years and we require 183 daily temperature observation per year in all sample years. Overall, we use more than 30 million daily temperature observations.

²² For firms that operate in more than one wholesale market region, weather volatility is calculated as the capacity-weighted average across all market regions in which a firm is active.

movements in electricity price volatility (with a F statistic of around 40). Therefore, because weather volatility is exogenous but correlated with electricity price volatility, it appears to be a valid instrument.

In Column (3) of Table 3, we analyze the impact of volatility on cash holdings using the instrumented values for volatility. As in the specifications reported in Table 2, we find a strong and positive impact of variations in the electricity price on firm liquidity. The estimates imply that a one-standard deviation increase in the instrumented electricity price volatility leads to an increase of cash holdings of about 1.2 percentage-points, which corresponds to a 23 percent increase. The magnitude is higher than for the reduced-form estimation in Column (1) and our main specifications in Table (2), where we find a ten percent relative increase. A potential concern with these results could be that weather affects not only wholesale price volatility, but also the production process of solar and wind power plants. To mitigate such concerns, we repeat the previous analysis but restrict the sample to firms for which solar and wind plants account for less than ten percent of their overall capacity. The estimates in Column (4) are similar to those reported above. Overall, these findings suggest that changes in electricity price volatility occurring because of weather fluctuations causally affect liquidity management decisions of firms.

4.4. Robustness Regarding Details of the Wholesale Electricity Market

One possible concern about the results is that not all utilities are price takers and some have the ability to affect wholesale prices through their bidding behavior during the auction process. Although such concerns are addressed somewhat by our instrumental variables estimates, we further assess whether bidding behavior could be affecting our results. First, we reestimate our equation excluding firms that account for more than 20% of the production capacity in a particular market and are likely to have significant market power and find similar results (see Panel A of Table 4). We also find similar results if we exclude firms with more than 10% of 1% market share, or interact their market share with volatility (i.e., volatility remains similar to before and the interaction term is insignificant).

Next, we exploit demand forecast data from U.S. market operators. This one-day ahead demand forecast, which is conducted and published by market operators, is independent of firms' actual bidding behavior. Because the data is not available before the third quarter of 2015, we rely on cross-sectional variation for this particular test. In Panel B of Table 4, we find that the standard deviation of hourly day-ahead demand forecasts, normalized by a market's average demand level, is positively related to the firm's level of cash holdings. This finding holds whether we use the demand forecast volatility for the specific quarter or the average volatility in a region. Assuming that cross-sectional patterns in the demand forecast volatility are relatively constant over time, we also find similar results if we use the average demand forecast volatility for the 2010 to 2016 period. Overall, this test shows that finding that higher demand volatility leads to increased cash holding suggests that the prior results on price volatility and cash holdings do not occur because of strategic bidding behavior.

Another possible concern is that electric utilities usually do not sell all their electricity in day-ahead markets, but also use long-term contracts. Since our analysis presumes that the firms' cash flows are a function of prices in day-ahead markets, it potentially misrepresents volatility for firms that rely on long-term contracts to a large extent. As a rough estimate of the importance of the day-ahead market in a particular region, we collect data on the electricity volume traded on a particular market and scale this by the total consumption of the region that is served by the market. Because of the difficulty in collecting this data, we use information as of 2010 or the closest year to 2010 for which data is available. In Panel C of Table 4, we then exclude firms located in markets which account for less than one-third, half, or two-thirds of the overall consumption. The results in this panel are consistent with those presented earlier, and the t-statistics increase when we exclude the regions for which day-ahead markets are less important.

As a second approach to understanding the extent to which the use of long-term contracts in addition to the day ahead market affects the interpretation of our results, we calculate the realized price volatility for U.S. firms, including the prices received through both the day-ahead market and long-term contracts. We estimate price volatility using data from FERC's EQR database, which contains almost all electricity transactions for U.S. utilities (see Section 3.4 for a detailed description). The realized price

volatility is calculated as the standard deviation of the prices of all transactions a firm conducts in a particular quarter scaled by the average price. In Columns (1) and (2) of Panel D, Table 4, we measure how well wholesale price volatility explains realized price volatility in the cross-section. We rely on cross-sectional evidence because of the relatively short time series of the realized price volatility data which starts in 2014. We find very high coefficients (close to one) with t-values above 30 for wholesale price volatility. These large coefficients imply that wholesale price volatility explains a large part of the realized price volatility. If we use the realized price volatility instead of wholesale price volatility in regressions that have cash holdings as dependent variables in Columns (3) and (4), we find that the coefficient is comparable to our main specifications using wholesale market volatility.

4.5. The Introduction of Wholesale Markets

The results we have presented suggest that electricity producing firms' cash holdings change with the volatility in wholesale electricity prices. Firms that face more volatile product prices compensate for this risk by holding more cash, as predicted by the precautionary theory of cash holdings. Holding cash is costly since it is tax disadvantaged in most countries and creates potential agency problems. The cost of holding the incremental cash can be thought of as a cost of deregulation because the establishment of wholesale markets for electricity is an important step in the deregulating process.

An implication of this view is that producing firms that operate in regions with wholesale markets for electricity should face more risk, and consequently hold more cash, than otherwise similar firms who operate in regulated markets. This prediction can be tested in our sample because 68 of our sample firms experienced the introduction of a wholesale market during our sample period. For those firms, we calculate their average cash holdings in the five-year period before and after the introduction of the wholesale market.²³ To avoid econometric problems due to serially correlated outcomes, we collapse the time-series so that we end up with one pre- and one post-period for each of those 68 firms (see Bertrand et al., 2004).

²³ For firms that operate in more than one market, we investigate the introduction of a wholesale market in the region with their largest production capacity.

We present estimates of this equation in Column (1) of Table 5. In Column (2), we additionally add control variables which are calculated as averages in the pre- or post-period. The variable of interest is a dummy variable that we call *Market*, which equals zero in the pre- and one in the post-period. The estimated coefficient on *Market* is positive, with a magnitude between .014 and .0.18. This coefficient implies that having to sell electricity through a wholesale market leads firms to increase cash holdings by approximately 1.5 percentage points, which would represent a 30 percent relative increase in an average firm's cash holdings.

In addition, we estimate equations using our main electricity price volatility measure and set it to zero for regions without wholesale markets in Columns (3) and (4). The advantage of this measure is that it considers the level of price risk in deregulated markets. The findings again show that higher product price risk leads to higher cash holdings. Overall, this analysis suggests that the introduction of wholesale markets as an important step in the deregulation process leads to higher cash holdings in the energy utilities industry, especially in markets where wholesale prices are more volatile. The holding cost of this additional cash can be thought of an additional cost of deregulation.

5. Hedging Opportunities, Operating Flexibility, and Lines of Credit

In this section, we explore how hedging opportunities and operating flexibility affect the way in which firms react to product price risk. At the end we investigate whether firms prefer holding cash or lines of credit to manage price risk.

5.1. The Role of Hedging Opportunities

Pre-selling part of their electricity production via futures, forwards, or bilateral contracts may protect firms from volatile wholesale prices, at least in the short run. In this sense, an alternative to holding cash as liquidity is to hedge the electricity price.²⁴ To evaluate the extent to which the possibility of hedging

²⁴ See, for instance, Giambona, Graham, Harvey, and Bodnar (2018) for a comprehensive overview on possible explanations why firms hedge.

price risk is a substitute for holding cash as a way to manage liquidity, we exploit the fact that the opportunities to hedge electricity price risk vary substantially across power markets.

We first construct a measure of firms' abilities to hedge in a particular market based a survey among European firms (see Section 3.4 for a data description). In this survey, energy firms are asked how they rate the ability to trade forward in a particular electricity market. Based on the responses, we classify every market as having a high or low hedgability. If a firm operates in more than one market, we use the capacity-weighted average of hedgability. In Column (1) of Table 6, Panel A, we estimate our base model for the sample for which data on hedgability is available as benchmark model.²⁵ When we split our sample firms into those operating in regions with low and high hedgability in Columns (2) and (3), we find that only those firms from regions with low hedgability increase cash holdings if price volatility goes up. Firms that can easily hedge the electricity price do not react to changes in price volatility at all. It is thus not surprising that the interaction between volatility and hedgability in Column (4) loads negatively. Firms' propensities to adjust their cash holdings in response to changes in product price volatility depend strongly on their ability to hedge price risk in derivative markets. In other words, the use of cash holdings for risk-management and hedging in derivative markets appear to be substitutes.

We complement the evidence from the survey among European firms using transaction-level data that is available for U.S. firms. In this setting, we separate sales that use market rates versus sales that use pre-determined fixed rates (e.g., bilateral contracts). For this purpose, we use EQR data (see Section 3.4 for a data description) and rely on the data item "type of rate". It takes the values ``Fixed", ``Formula", ``Electric Index", and ``RTO/ISO".²⁶ The first measure is a region-quarter level measure that is calculated as the

²⁵ We include hedgability as control but do not report the coefficient. Hedgability is not dropped in the firm-fixed effects regressions despite the fact that it is time-invariant because firms can operate in multiple markets. If the capacity in the different markets changes over time, the firm-level aggregated value of hedgability can change.

²⁶ The EQR requirement guideline specifies that "If the price is the result of an RTO/ISO market and the sale is made to the RTO/ISO, its rate type is 'RTO/ISO.' If no variables are used to determine the rate, it should be marked as 'fixed.' This would include transactions where the specific price is stated or a specific price with a predetermined escalator is provided (e.g., \$35.00/MWh, increasing by 2 percent each year). Under a transaction classified with the rate type 'fixed,' both parties would know on the trade date the exact price of the product(s) in that transaction." (Source: Order No. 768, Paragraph 107)". Electric index is an index that ``references an RTO/ISO pricing point". Formula means that " the price in the transaction is otherwise determined by a formula, including a formula that uses indices that do not describe specific electric prices, such as a cost of living index or coal or natural gas prices".

volume-weighted fraction of trades that use fixed or formula pricing relative to all trades. If this fraction is high in a particular market and quarter, it means that many firms are selling electricity for prices that are independent of the RTO/ISO rates. This variable therefore measures how common hedging is in a particular market and quarter. We directly use this market-quarter level measure for firms that only operate in one market or calculate the capacity-weighted average for firms operating in multiple markets.

The results are reported in Panel B of Table 6. In Column (1), we estimate our main specification and control for hedgability as benchmark model. In Columns (2) and (3), we split the sample in firms with low and high hedgability. where a region-quarter is classified as having low (high) hedgability if the fraction of trades that use fixed or formula pricing is below (above) the median. We find that the coefficient estimate for electricity price volatility is 0.01 for regions with low hedgability (marginally insignificant), and -0.0007 for regions with high hedgability. When we interact hegability with the electricity price volatility, the impact of volatility on cash holdings is substantially reduced by hedgability.

Our second measure for the U.S. setting is a firm-level measure which uses the same calculation approach as the region-level measure, but does not aggregated the data on the market level. The results, presented in Panel C of Table 6, are in line with the market-level findings: only firms with a low fraction of fixed-price contracts react to changes in the electricity price volatility. Consistent with Hypothesis 2, both the results from the European survey data and the findings based on U.S. transaction data suggest that hedging through derivative markets or bilateral contracts is a substitute for holding cash.

5.2. The Role of Operating Flexibility

We evaluate whether the method of production used by our sample firms affects their response to changes in price volatility. To do so, we use our annual data on production assets to calculate the degree of operating flexibility for each firm in each year using the production technologies of single power plants. We define *FLEXIBILITY* as the generation capacity of flexible power plants, scaled by the total generation capacity, for every firm and year. Gas and oil-fired power plants are considered "flexible" because they have the fastest run-up time and the lowest ramp-up cost while coal, lignite, nuclear, or waste are costly to

stop and start so are classified as "not flexible."²⁷ Similar to GDP, we use the lagged annual value of flexibility because the contemporaneous value would be forward looking for quarters one to three.

To assess whether operating flexibility affects the way in which firms react to product price risk, we start by adding *FLEXIBILITY* as an additional control variable in Column (1) of Table 7. The estimates indicate that operating flexibility itself has little impact on firms' cash holdings. Next, we split the sample in two subsamples of firms with low operating flexibility in Column (2) and high operating flexibility in Column (3). Consistent with Hypothesis 3, the results suggest that the impact of price volatility on cash holdings comes primarily from the sample of firms with relatively inflexible production technologies. For those baseload producers, the coefficient on volatility is 0.0074 while for firms with high levels of operating flexibility, the coefficient is 0.0029, which is not statistically significantly different from zero. In Column (4), we use a specification with an interaction term between operation flexibility and product price risk, and find a statistically significant negative coefficient on the interaction term.

Overall, the positive impact of volatility on cash holdings appears to be driven by baseload producers with inflexible production technologies. In contrast to flexible firms, these energy utilities tend to have high fixed cost and bid near zero because they cannot easily adjust their production. For this reason, those firms have a high exposure to electricity price volatility, so appear to and build up liquidity buffers if the electricity price is highly volatile. Operating flexibility and cash holdings appear to be substitutes for one another in their effect on firms' ability to hedge product price or, more generally, cash flow uncertainty. The Internet Appendix presents additional tests that address concerns about the special character of wind and solar plants, other differences between flexible and inflexible plants such as environmental liability exposure, and endogeneity.

 $^{^{27}}$ See Reinartz and Schmid (2016) for more details about the flexibility of individual production technologies. We ignore wind and solar plants for the calculation of *FLEXIBILITY*, i.e., we do not consider them for the calculation of the total generation capacity. Classifying these technologies as flexible or inflexible is not straightforward, there are often subsidies for wind and solar plants, and firms may need to invest in R&D when operating those assets.

5.3. Cash Holdings versus Lines of Credit

Finally, we analyze whether firms prefer holding cash or credit lines as response to higher product price risk using data on credit lines from *Market Intelligence*. This database offers information on total and drawn credit lines for U.S. firms. In Table 8, we start by analyzing how product price risk affects total credit lines. The estimates presented in Column 1 suggest that the impact is positive. This result that firms demand more credit lines from banks when product price risk increases, and banks, at least partly, fulfill this demand. When we turn to drawn credit lines in Column 2, we find that energy firms use more credit lines when product price risk increases. Thus, both credit lines and cash holdings seem to be used by those firms in response to higher uncertainty.

However, those bank credit lines are not be perfect substitutes for cash. Acharya et al. (2013) present a model in which firms with higher aggregate risk should rely more on cash instead of credit lines. The idea is that banks cannot be able to provide liquidity in all times, especially after large economy-wide shocks. In our setting, higher product price risk is unlikely to be correlated with shocks to the overall economy. However, product price risk increases the riskiness of the energy sector within an economy.

We examine whether product price risk as a sector-specific risk also affects firms' choice between cash and lines of credit. One likely mechanism is that banks increase the price of credit lines if product price risk increases. We follow Acharya et al. (2013) and calculate two variables: total credit lines scaled by cash (plus total credit lines) and unused credit lines scaled by cash (plus unused credit lines). The results in Table 8 indicate that firms facing higher product price risk rely more on cash than on credit lines. This finding is in line with the view that not only economy-wide shocks, but also industry-wide risk can lead to a relative preference of firms for cash over credit lines.

6. Conclusion

One of the most important decisions financial managers make concerns the liquidity of the firm's balance sheet. Holding cash is costly for tax and other reasons, while at the same time insulating the firm from the obligation to raise external capital should there be an unexpected cash shortfall. We evaluate firms'

decisions to hold cash by isolating one specific source of risk faced by firms in one industry: the risk faced by electricity producing firms when electricity wholesale prices are volatile.

Our estimates, which are based on time-series variation of price risk within firms, imply that firms' cash holdings are positively related to product price fluctuations. More precisely, our main estimates imply that a one-standard deviation increase in price volatility leads to an increase of cash holdings of about 0.4 percentage points, which corresponds to a seven percent relative change. This pattern is consistent with the view that firms' liquidity choices reflect the expected costs of price risk. To isolate the channel through which wholesale electricity price volatility affects producing firms' liquidity choices, we rely on the fact that movements in electricity prices often occur because of weather-induced demand changes. Using an instrument based on the volatility of a region's temperatures, we find the same pattern as when we use our baseline models for estimation, suggesting that price risk causally affects firms' cash policy in the manner suggested by the precautionary theory of liquidity.

Wholesale price volatility appears to increase the risk faced by electricity producers, who compensate by holding more cash on their balance sheets. This additional risk faced by electricity producers is a consequence of the deregulatory environment because the introduction of wholesale markets is an important step in the deregulating process. As a test of this idea, we compare the cash holdings of firms operating in regulated markets to those selling their electricity in volatile wholesale markets. Consistent with the notion that deregulation increases the risk faced by electricity producers, our results suggest that firms selling on wholesale markets hold about 30% more cash than otherwise identical firms in regulated markets.

When we analyze the role of firms' operating flexibility, we find that firms with more inflexible production technologies tend to hold more cash in markets with more volatile electricity prices. In contrast to those baseload producers, product price risk has little impact on firms' cash holdings if their operating flexibility is high. In addition, the ability of firms to hedge price risk by selling a portion of their electricity in advance varies across markets. Being able to hedge in this manner is potentially a substitute for holding

liquidity. Consistent with this argument, we find that the existence of a more liquid hedging market reduces the impact of price risk on electricity producers' liquidity choices.

Overall, our findings suggest that product price volatility can be an important factor affecting firms' liquidity choices. Firms' operating flexibility and the liquidity of derivative markets are major factors affecting this risk. The electricity producing industry provides a useful laboratory for studying liquidity management issues, since firm only sell one completely homogenous good and we can observe high-frequency product prices and their production assets. Although our analysis focuses on electricity producing firms, it is likely that product price risk affects liquidity management choices in a similar manner in other industries as well.

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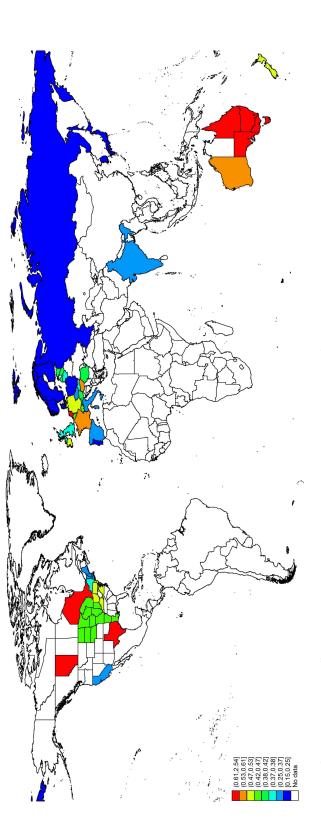
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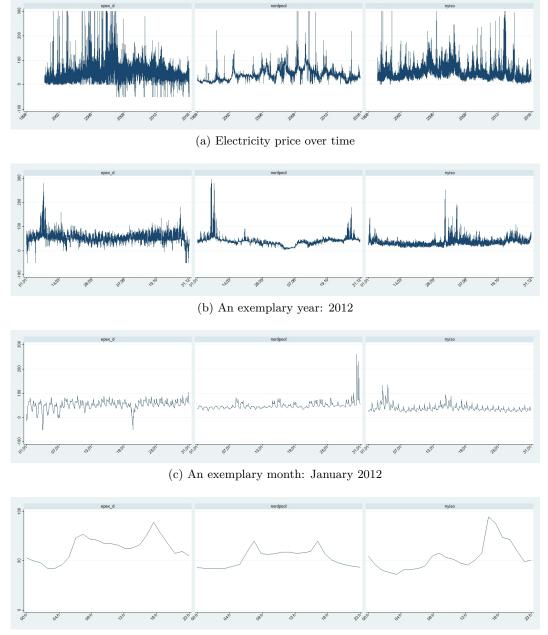
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(d) An exemplary day: January 15, 2012

Figure 2: This figure shows hourly electricity prices in US\$ per MWh for three selected markets: EPEX_D (Germany), Nordpool (Northern Europe), and NYISO (state of New York). The whole time series is shown in Figure (a). The prices for an exemplary year (2012), month (January 2012) and day (January 15, 2012) are shown in Subfigures (b), (c), and (d). For this illustration, prices are capped at minus 50 and 300 US\$ per MWh. An overview on all included markets can be found in Appendix B.

Variable	\mathbf{N}	mean	p25	$\mathbf{p50}$	$\mathbf{p75}$	\mathbf{SD}	
Cash	5,711	0.05	0.01	0.03	0.07	0.06	
Volatiltiy	5,784	0.46	0.23	0.33	0.50	0.56	
Log(Volatility)	5,784	-1.05	-1.48	-1.11	-0.69	0.66	
Weather volatility	5,736	4.67	3.26	4.42	5.80	1.81	
Log(Weather volatility)	5,736	1.46	1.18	1.49	1.76	0.41	
Flexibility	5,784	0.39	0.19	0.37	0.56	0.27	
Assets (mio USD)	5,783	24,022	$3,\!942$	$13,\!005$	33,764	$28,\!486$	
Assets (log)	5,783	16.16	15.19	16.38	17.33	1.51	
Cash flow	5,718	0.03	0.02	0.03	0.04	0.04	
Leverage	5,712	0.44	0.32	0.41	0.58	0.18	
GDP (US\$ per capita)	5,735	10.45	10.53	10.75	10.81	0.75	
Panel B: Correlation of Volatility Measures							

Panel A: Firm-level Descriptives

E: $Log(Volatility_{std. diff})$

ιy В \mathbf{C} D Е А A: Log(Volatility) 1.00**B**: Volatility 0.791.00C: Log(Volatility_{price}) 0.870.681.00D: Log(Volatility_{diff}) 0.930.800.651.00

0.91

Panel A presents descriptive statistics averaged over all firm-quarters in our sample. Reported are the number of observations (N), mean value, 25% percentile, median, 75% percentile, and standard deviation (SD). Panel B shows the correlation between the different measures for electricity price volatility. A detailed description of all variables can be found in Appendix A.

0.75

0.82

0.91

1.00

Column	1	2	3	4 0.0055*** (3.12)	
$\mathrm{Log}(\mathrm{Volatility}_t)$	0.0072^{***} (3.88)	0.0073^{***} (3.94)	0.0051^{***} (3.01)		
$Log(assets_t)$	-0.0040***	-0.0037***	-0.0098	-0.0096	
	(-2.81)	(-2.80)	(-1.42)	(-1.38)	
Cash flow $_t$	-0.022	-0.031	-0.016	-0.017	
	(-0.42)	(-0.61)	(-0.50)	(-0.49)	
$Leverage_t$	-0.018	-0.014	-0.018	-0.016	
	(-0.61)	(-0.49)	(-0.66)	(-0.61)	
$Log(GDP \text{ per capita}_{t-1y})$	-0.063***	-0.065***	-0.098**	-0.098**	
	(-3.11)	(-3.02)	(-2.35)	(-2.36)	
Firm-FE	no	no	yes	yes	
Country-FE	yes	yes	n/a	n/a	
Year-FE	yes	yes	yes	yes	
Quarter-FE	yes	yes	yes	yes	
Country x Quarter FE	no	yes	no	yes	
Observations	5,558	$5,\!556$	5,551	$5,\!549$	
Adj. \mathbb{R}^2	0.41	0.41	0.68	0.68	

Table 2: Explaining Cash Holdings as a Function of Wholesale Price Volatility

The dependent variable is quarterly cash holdings normalized by total assets. Volatility is defined as the standard deviation of hourly electricity prices in a fiscal quarter, normalized by a market's average electricity price level. T-statistics based on Huber/White robust standard errors clustered by countries are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Column	1	2	3	4
	all	all	all	wind/solar $< 10\%$
Model	red. form	IV 1st	IV 2nd	IV 2nd
$Log(Weather volatility_t)$	0.0095***	0.52^{***}		
	(3.02)	(6.13)		
$\mathrm{Log}(\mathrm{Volatility}_t)_{instr}$			0.018^{**}	0.020***
			(2.66)	(2.99)
$Log(assets_t)$	-0.0096	0.029	-0.010	-0.0100
	(-1.40)	(0.66)	(-1.49)	(-1.29)
Cash flow _t	-0.021	-0.045	-0.020	-0.024
	(-0.60)	(-0.21)	(-0.57)	(-0.70)
$Leverage_t$	-0.018	-0.053	-0.017	-0.016
	(-0.66)	(-0.32)	(-0.65)	(-0.56)
$Log(GDP \text{ per capita}_{t-1y})$	-0.14***	0.80	-0.15***	-0.16***
	(-3.78)	(0.77)	(-3.49)	(-3.21)
Firm-FE	yes	yes	yes	yes
Year-FE	yes	yes	yes	yes
Quarter-FE	yes	yes	yes	yes
Country x Quarter FE	yes	yes	yes	yes
Observations	5,501	5,501	5,501	4,886
K-P rk Wald F	n/a	37.63		60.22

Table 3: Instrumenting Wholesale Price Volatility using Weather Volatility

This table shows instrumental variable regressions that use quarterly weather volatility as an instrument for quarterly electricity price volatility. Weather volatility is defined as the standard deviation of daily average temperatures in a fiscal quarter. Electricity price volatility is defined as the standard deviation of hourly electricity prices in a fiscal quarter, normalized by a market's average electricity price level. The sample for this analysis consists of all firms in Columns 1 to 3. In Column 4, only firms with less than ten percent wind and solar generation capacity are considered. First-stage instrumental variable regressions are reported in Column 2, with log(volatility) as the dependent variable. Column 1 shows a reduced form regression and Columns 2 and 4 show second-stage instrumental variable regressions with quarterly cash holdings normalized by total assets as dependent variables. K-P rk Wald F stands for Kleibergen-Paap rk Wald F statistic. T-statistics based on Huber/White robust standard errors clustered by countries are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Panel A: Market Power				
Column	1	2	3	4
Market share (capacity)	< 20%	< 10%	< 1%	all
$Log(Volatility_t)$	0.0056***	0.0054**	0.0060**	0.0049***
	(3.10)	(2.63)	(2.10)	(2.80)
Market share $(capacity)_t$				0.041***
				(2.84)
$Log(Vol_t) \ge market \ share_t$				0.0028
				(0.36)
Controls	yes	yes	yes	yes
Firm-FE	yes	yes	yes	yes
Year-FE	yes	yes	yes	yes
Quarter-FE	yes	yes	yes	yes
Country x Quarter FE	yes	yes	yes	yes
Observations	4,860	4,144	$1,\!921$	$5,\!520$
$Adj. R^2$	0.67	0.67	0.71	0.68
Panel B: Demand Volatility (U.S. only, cr	oss-sectional)		
Column	1	2	3	4
Sample		starts $2015Q3$		starts 2010
$Log(Demand forecast vol_t)$	0.051^{***}	0.042**		
	(4.79)	(3.10)		
$Log(Demand forecast vol_{avg})$			0.099^{***}	0.10**
			(3.29)	(2.47)
Controls	no	yes	yes	yes
Firm-FE	no	no	no	no
Year-FE	yes	yes	yes	yes
Quarter-FE	yes	yes	yes	yes
Observations	256	255	259	1,227
Adj. \mathbb{R}^2	0.027	0.28	0.28	0.20

Table 4: Exploring the Role of Institutional Details

 $continued \ on \ next \ page$

Column	1	2	3	4
DAM-to-consumption ₂₀₁₀	$\geq 1/3$	≥ 0.5	$\geq 2/3$	all
$Log(Volatility_t)$	0.0038**	0.0045***	0.0041***	0.0059***
$\log(10 \operatorname{Ref}(t))$	(2.77)	(3.22)	(4.08)	(3.21)
$\text{Log}(\text{Vola}_t) \ge \frac{\text{DAM}_{2010}}{\text{consumption}_{2010}}$	(=)	(0.22)	(1100)	-0.0017
-3(1) consumption ₂₀₁₀				(-0.43)
Controls	yes	yes	yes	yes
Firm-FE	yes	yes	yes	yes
Year-FE	yes	yes	yes	yes
Quarter-FE	yes	yes	yes	yes
Country x Quarter FE	yes	yes	yes	yes
Observations	4,043	$3,\!684$	3,303	$5,\!224$
Adj. \mathbb{R}^2	0.67	0.64	0.61	0.70
Adj. R ² Panel D: Realized Price Vola				0.70
·				0.70
Panel D: Realized Price Vola	tility (U.S. o	nly, cross-sec	tional)	4
Panel D: Realized Price Volar Column	tility (U.S. o	nly, cross-sec	tional) 3	4
Panel D: Realized Price Volat Column Dependent	tility (U.S. o 1 Log(Real	nly, cross-sec 2 ized Vol _t)	tional) 3 Ca	4
Panel D: Realized Price Volat Column Dependent	tility (U.S. o 1 Log(Real 0.88***	nly, cross-sec 2 ized Vol_t) 0.86^{***}	tional) 3 Ca 0.0055***	4
Panel D: Realized Price Volat Column Dependent $Log(Volatility_t)$	tility (U.S. o 1 Log(Real 0.88***	nly, cross-sec 2 ized Vol_t) 0.86^{***}	tional) 3 Ca 0.0055***	4 sh
Panel D: Realized Price Volat Column Dependent $Log(Volatility_t)$	tility (U.S. o 1 Log(Real 0.88***	nly, cross-sec 2 ized Vol_t) 0.86^{***}	tional) 3 Ca 0.0055***	4 sh 0.0083**
Panel D: Realized Price Volat Column Dependent $Log(Volatility_t)$ $Log(Realized Vol_t)$	tility (U.S. o 1 Log(Real 0.88*** (33.9)	nly, cross-sec 2 ized Vol _t) 0.86^{***} (38.7)	tional) 3 Ca 0.0055*** (4.88)	4 sh 0.0083** (3.32)
Panel D: Realized Price Volat Column Dependent $Log(Volatility_t)$ $Log(Realized Vol_t)$ Controls	tility (U.S. o 1 Log(Real 0.88*** (33.9)	nly, cross-sec 2 ized Vol_t) 0.86*** (38.7) yes	tional) 3 Ca 0.0055*** (4.88) yes	4 sh 0.0083** (3.32) yes
Panel D: Realized Price Volat Column Dependent $Log(Volatility_t)$ $Log(Realized Vol_t)$ Controls Firm-FE	tility (U.S. o 1 Log(Real 0.88*** (33.9) no no	nly, cross-sec 2 ized Vol _t) 0.86*** (38.7) yes no	tional) 3 Ca 0.0055*** (4.88) yes no	4 sh 0.0083** (3.32) yes no
Panel D: Realized Price Volat Column Dependent Log(Volatility _t) Log(Realized Vol _t) Controls Firm-FE Year-FE	tility (U.S. o 1 Log(Real 0.88*** (33.9) no no yes	2 ized Vol _t) 0.86*** (38.7) yes no yes	tional) 3 Ca 0.0055*** (4.88) yes no yes	4 sh 0.0083** (3.32) yes no yes
Panel D: Realized Price Volat Column Dependent $Log(Volatility_t)$ $Log(Realized Vol_t)$ Controls Firm-FE Year-FE Quarter-FE	tility (U.S. o 1 Log(Real 0.88*** (33.9) no no yes yes	2 ized Vol _t) 0.86*** (38.7) yes no yes yes	tional) 3 Ca 0.0055*** (4.88) yes no yes yes	4 sh 0.0083** (3.32) yes no yes yes

Table 4 continued

 $continued \ on \ next \ page$

Table 4 continued

In the base specification, the dependent variable is quarterly cash holdings normalized by total assets and volatility is defined as the standard deviation of hourly electricity prices in a fiscal quarter, normalized by a market's average electricity price level. The unreported control variables are identical to those in Table 2.

In Panel A, we explore the role of firms' market power. In Column 1, only firms which account for less than 10% of the total capacity in a market and year are included. The market share of the company is interacted with volatility in Column 2. In Column 3, the ten largest firms in a market and year are excluded. The rank of the firm in terms of its capacity in a market and year is interacted with volatility in Column 4.

In Panel B, the main independent variable is the volatility of the demand forecast, which is defined as the standard deviation of hourly day-ahead demand forecast, normalized by a market's average demand forecast. The demand forecast is conduced on a market level by the market operator (e.g., PJM) and obtained from the U.S. Energy Information Administration. Only U.S. firms are included for this test because demand forecast data is not available for other countries.

In Panel C, we explore the role of the market size, measured as the annual volume of a country's day-ahead market in 2010 scaled by its total electricity consumption in that year. In Columns 1 to 3, we only include firms if the capacity-weighted average of this market size is above one-third, 50%, or two-thirds. In the last column, we interact this measures with volatility.

In Panel D, we investigate realized price volatility, which is defined as the standard deviation of transaction prices of a firm within a particular quarter. The data comes from FERC's EQR database and is only available for U.S. firms. In the first two columns, realized price volatility is used as the dependent variable, while cash is the dependent variable in the latter two columns.

T-statistics based on Huber/White robust standard errors clustered by countries (Panels A and C) or markets (Panels B and D) are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Column	1	2	3	4
	collapsed	pre/post	fı	ıll
Market $(dummy)_t$	0.014**	0.018**		
	(2.34)	(2.24)		
$\mathrm{Log}(\mathrm{Volatility}_{zero,t})$			0.0060^{***}	0.0058^{***}
			(3.24)	(3.08)
$Log(assets_t)$		-0.018	-0.0049	-0.0050
		(-0.62)	(-0.79)	(-0.79)
Cash flow $_t$		-0.063	0.049	0.048
		(-0.25)	(0.90)	(0.87)
$Leverage_t$		0.030	-0.076***	-0.076***
		(0.55)	(-2.99)	(-2.99)
$Log(GDP \text{ per capita}_{t-1y})$		-0.028	-0.025	-0.024
		(-0.52)	(-1.40)	(-1.36)
Firm-FE	yes	yes	yes	yes
Year-FE	n/a	n/a	yes	yes
Quarter-FE	n/a	n/a	yes	yes
Country x Quarter FE	n/a	n/a	no	yes
Observations	136	126	$10,\!699$	$10,\!695$
Adj. \mathbb{R}^2	0.71	0.74	0.63	0.63

Table 5: The Introduction of Wholesale Markets and Cash Holdings

The dependent variable is quarterly cash holdings normalized by total assets. In Columns (1) and (2), we collapse the dataset in a pre- and post-period which consist of the five years before and after the introduction of a wholesale market for electricity. Market is a dummy variable which equals one if a wholesale market for electricity exists. Volatility_{zero} is defined as the standard deviation of hourly electricity prices in a fiscal quarter, normalized by a market's average electricity price level; for regions without a wholesale market for electricity, this variable is set to zero. The year in which a market is introduced is excluded in all analyses. All models are firm fixed effects regressions. T-statistics based on Huber/White robust standard errors clustered by countries are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Column	1	2	3	4
Sample	all	low hedg.	high hedg.	all
$\operatorname{Log}(\operatorname{Volatility}_t)$	0.0047	0.013**	0.000073	0.011*
	(1.23)	(2.52)	(0.021)	(1.83)
Hedgability $(survey)_{2008}$	n/r			n/r
$Log(Volatility_t) \ge hedgability$				-0.011^{*} (-1.76)
Controls	yes	yes	yes	yes
Firm-FE	no	yes	yes	yes
Year-FE	yes	yes	yes	yes
Quarter-FE	yes	yes	yes	yes
Country x Quarter FE	yes	yes	yes	yes
Observations	1,765	897	859	1,765
			0.00	
$Adj. R^2$	0.65	0.60	0.66	0.65
Adj. R ² Panel B: Fraction of transaction				
Panel B: Fraction of transactio	ons with fix	ed prices (U.S. only, m	arket-leve
Panel B: Fraction of transactic	ons with fix	ed prices (U.S. only, m	arket-leve 4 all
Panel B: Fraction of transaction Column Sample	ons with fix 1 all	ed prices (2 low hedg.	U.S. only, m 3 high hedg.	arket-leve 4 all
Panel B: Fraction of transaction Column Sample	ons with fix 1 all 0.0041**	eed prices (2 low hedg. 0.0096	U.S. only, m 3 high hedg. -0.00068	arket-leve 4 all 0.0077** (2.34)
Panel B: Fraction of transaction Column Sample Log(Volatility _t)	ns with fix 1 all 0.0041** (2.44)	eed prices (2 low hedg. 0.0096	U.S. only, m 3 high hedg. -0.00068	arket-leve 4 all 0.0077** (2.34)
Panel B: Fraction of transaction Column Sample Log(Volatility _t)	ns with fix 1 all 0.0041** (2.44) -0.066*	eed prices (2 low hedg. 0.0096	U.S. only, m 3 high hedg. -0.00068	arket-leve 4 all 0.0077** (2.34) -0.12**** (-3.97)
Panel B: Fraction of transactic Column Sample $Log(Volatility_t)$ Hedgability (fixed prices, region) _t	ns with fix 1 all 0.0041** (2.44) -0.066*	eed prices (2 low hedg. 0.0096	U.S. only, m 3 high hedg. -0.00068	arket-leve 4 all 0.0077** (2.34) -0.12**** (-3.97)
Panel B: Fraction of transactic Column Sample $Log(Volatility_t)$ Hedgability (fixed prices, region) _t	ns with fix 1 all 0.0041** (2.44) -0.066*	eed prices (2 low hedg. 0.0096	U.S. only, m 3 high hedg. -0.00068	arket-leve 4 all 0.0077** (2.34) -0.12*** (-3.97) -0.045**
Panel B: Fraction of transactic Column Sample $Log(Volatility_t)$ Hedgability (fixed prices, region) _t $Log(Volatility_t)$ x hedgability	ns with fix 1 all 0.0041** (2.44) -0.066* (-1.86)	2 low hedg. 0.0096 (1.70)	U.S. only, m 3 high hedg. -0.00068 (-0.27)	arket-leve 4 all 0.0077** (2.34) -0.12*** (-3.97) -0.045** (-2.83)
Panel B: Fraction of transaction Column Sample $Log(Volatility_t)$ Hedgability (fixed prices, region) _t $Log(Volatility_t)$ x hedgability Controls	pms with fix 1 all 0.0041** (2.44) -0.066* (-1.86) yes	eed prices (2 low hedg. 0.0096 (1.70)	U.S. only, m 3 high hedg. -0.00068 (-0.27) yes	arket-leve 4 all 0.0077** (2.34) -0.12**** (-3.97) -0.045** (-2.83) yes
Panel B: Fraction of transaction Column Sample Log(Volatility _t) Hedgability (fixed prices, region) _t Log(Volatility _t) x hedgability Controls Firm-FE	pns with fix 1 all 0.0041** (2.44) -0.066* (-1.86) yes yes	eed prices (2 low hedg. 0.0096 (1.70)	U.S. only, m 3 high hedg. -0.00068 (-0.27) yes yes	arket-leve 4 all 0.0077** (2.34) -0.12*** (-3.97) -0.045** (-2.83) yes yes
Panel B: Fraction of transactic Column Sample $Log(Volatility_t)$ Hedgability (fixed prices, region) _t $Log(Volatility_t) \times hedgability$ Controls Firm-FE Year-FE	pns with fix 1 all 0.0041** (2.44) -0.066* (-1.86) yes yes yes	eed prices (2 low hedg. 0.0096 (1.70) yes yes yes	U.S. only, m 3 high hedg. -0.00068 (-0.27) yes yes yes yes	arket-leve 4 all 0.0077** (2.34) -0.12*** (-3.97) -0.045** (-2.83) yes yes yes
Panel B: Fraction of transactic Column Sample $Log(Volatility_t)$ Hedgability (fixed prices, region) _t $Log(Volatility_t)$ x hedgability Controls Firm-FE Year-FE Quarter-FE	pms with fix 1 all 0.0041** (2.44) -0.066* (-1.86) yes yes yes yes yes	eed prices (2 low hedg. 0.0096 (1.70) yes yes yes yes yes	U.S. only, m 3 high hedg. -0.00068 (-0.27) yes yes yes yes yes	arket-leve 4 all 0.0077** (2.34) -0.12*** (-3.97) -0.045** (-2.83) yes yes yes yes

 Table 6: Do Hedging Opportunities Mitigate the Impact of Price Risk on Cash Holdings?

 $continued \ on \ next \ page$

Table 6 d	continued
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Panel C: Fraction of transactions with fixed prices (U.S. only, firm-level)				rm-level)
Column	1	2	3	4
Sample	all	low hedg.	high hedg.	all
$\mathrm{Log}(\mathrm{Volatility}_t)$	0.0036*	0.0045	0.00053	0.0048**
	(2.28)	(1.31)	(0.54)	(2.51)
Hedgability (fixed prices, firm) _t	-0.0086			-0.013*
	(-1.53)			(-2.08)
$Log(Volatility_t) \ge hedgability$				-0.0036**
				(-2.78)
Controls	yes	yes	yes	yes
Firm-FE	yes	yes	yes	yes
Year-FE	yes	yes	yes	yes
Quarter-FE	yes	yes	yes	yes
Market x Quarter FE	yes	yes	yes	yes
Observations	436	215	214	436
Adj. \mathbb{R}^2	0.85	0.91	0.51	0.85

The dependent variable is quarterly cash holdings normalized by total assets. Volatility is defined as the standard deviation of hourly electricity prices in a fiscal quarter, normalized by a market's average electricity price level. In Panel A, hedgability is based on survey data among European firms. In Panels B and C, we use individual translation data from FERC's EQR database to calculate the fraction of transactions that use fixed prices within a market-region (Panel B) or within a firm (Panel C). More details are provided in Appendix A. The unreported control variables are identical to those in Table 2. n/r stands for not reported. T-statistics based on Huber/White robust standard errors clustered by countries (Panel A) or markets (Panels B and C) are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Column	1	2	3	4
Sample	all	low flex	high flex	all
$\operatorname{Log}(\operatorname{Volatility}_t)$	0.0055***	0.0074***	0.0029	0.010***
	(3.13)	(3.20)	(1.13)	(3.25)
$Flexibility_{t-1y}$	-0.0019			-0.012
	(-0.19)			(-1.12)
$Log(Volatility_t) \ge flex_{t-1y}$				-0.012**
				(-2.38)
$Log(assets_t)$	-0.0095	0.012	-0.024***	-0.0095
	(-1.35)	(1.25)	(-3.65)	(-1.36)
Cash flow _{t}	-0.017	-0.039	0.0042	-0.018
	(-0.49)	(-0.91)	(0.13)	(-0.53)
$Leverage_t$	-0.017	-0.031	-0.020	-0.016
	(-0.61)	(-0.97)	(-0.55)	(-0.60)
$Log(GDP \text{ per capita}_{t-1y})$	-0.098**	-0.071*	-0.19**	-0.097**
	(-2.37)	(-1.94)	(-2.78)	(-2.36)
Firm-FE	yes	yes	yes	yes
Year-FE	yes	yes	yes	yes
Quarter-FE	yes	yes	yes	yes
Country x Quarter FE	yes	yes	yes	yes
Observations	$5,\!549$	2,775	2,766	$5,\!549$
Adj. \mathbb{R}^2	0.68	0.69	0.70	0.68

Table 7: Does Operating Flexibility Mitigate the Impact of Price Risk on Cash Holdings?

The dependent variable is quarterly cash holdings normalized by total assets. Volatility is defined as the standard deviation of hourly electricity prices in a fiscal quarter, normalized by a market's average electricity price level. Flexibility is defined as the generation capacity of gas and oil-fired power plants, scaled by total capacity (without consideration of wind and solar capacity). Firms are split into low and high flex in Columns 2 to 3 based on their flexible generation capacity. All models are firm fixed effects regressions. T-statistics based on Huber/White robust standard errors clustered by countries are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Column Dependent	1 Total LC	2 Used LC	3 Total LC-to-cash	4 Unused LC-to-cash
$\mathrm{Log}(\mathrm{Volatility}_t)$	0.0050^{**} (2.89)	0.0024^{*} (1.81)	-0.026* (-1.92)	-0.030* (-1.97)
Controls	yes	yes	yes	yes
Firm-FE	yes	yes	yes	yes
Year-FE	yes	yes	yes	yes
Quarter-FE	yes	yes	yes	yes
Market x Quarter FE	yes	yes	yes	yes
Observations	2,577	2,337	$2,\!689$	$2,\!435$
Adj. \mathbb{R}^2	0.72	0.58	0.55	0.57

Table 8: Do Firms use Lines of Credit (LC) as Response to Price Volatility (U.S. only)?

The dependent variables are total credit lines scaled by total assets, used credit lines scaled by total assets, total credit lines scaled by the sum of total credit lines and cash, and unused credit lines scaled by the sum of unused credit lines and cash. Volatility is defined as the standard deviation of hourly electricity prices in a fiscal quarter, normalized by a market's average electricity price level. The unreported control variables are identical to those in Table 2. T-statistics based on Huber/White robust standard errors clustered by markets are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Appendix

Variable	Description
Main Variables	
Cash	Cash & short term investments scaled by total assets. Source: Market Intel-
	ligence data items $\left[246026\right]$ and $\left[132264\right]$ for U.S./Canadian firms and World-
	scope data items $[02001]$ and $[02999]$ for all other firms.
Volatility	Standard deviation of hourly electricity prices, normalized by a market's
	average electricity price level. Electricity prices are in US\$ per megawatt hour $% \mathcal{A}$
	(MWh). Local electricity prices are converted to US\$ using daily exchange
	rates. Volatility is calculated during a firm's fiscal quarter; for U.S. and
	Canadian firms before 2004, it is calculated for fiscal years. For firms that
	operate in more than one market, volatility is the capacity-weighted average
	of the volatility in each day-ahead market in which the firm is active . Source:
	Own calculations based on hourly electricity prices.
Weather volatility	Standard deviation of daily temperatures. Daily temperatures are calculated
	as the average across all weather stations within an electricity market. Only
	stations with at least 183 annual observations in all sample years are consid-
	ered. Weather volatility is calculated during a firm's fiscal quarter; for U.S.
	and Canadian firms before 2004, it is calculated for fiscal years. For firms
	that operate in more than one market, weather volatility is the capacity-
	weighted average of the weather volatility in each market in which the firm
	is active. Source: Own calculations based on data from the daily global
	historical climatology network (cf. Menne et al., 2012).
Flexibility	Generation capacity of gas and oil-fired power plants, scaled by total capacity.
	Wind and solar power plants are ignored for the calculation of total capacity.
	Source: Own calculations based on WEPP and Market Intelligence database.
Hedgability (survey)	Ability to trade forward in a particular electricity market based on a survey
	among European firms which was conducted in early 2008 (Moffatt Asso-
	ciates Partnership: "Review and Analysis of EU wholes ale energy markets",
	prepared for the European Commission DG TREN). Firms can respond that
	the ability to trade forward is "strong", "moderate", or "weak". We create
	the dummy variable hedgability which equals one if more firms responded
	that the ability to trade forward is "strong" rather than "weak". Examples
	for markets with strong (weak) hedgability are Nordpool or Germany (Italy
	or Portugal). For firms that operate in more than one market, hedgability
	is the capacity-weighted average of the hedgability in each market in which
	the firm is active. Source: Own calculations based on survey data.

Appendix A: Definition c	of Variables
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	Definition of Variables - continued
Variable	Description
Hedgability (EQR,market)	Fraction of transactions that use market-based rates in a particular market region. Data comes from the FERC's Electric Quarterly Reports (EQR) database and coves all electricity transactions within the U.S. (with the ex- ception of ERCOT). The data item "type of rate" is available from 2013Q3 and takes the value "Fixed", "Formula", "Electric Index", or "RTO/ISO". Hedgability is the volume of trades in a region and quarter that use rates which do not depend on the market price of electricity (i.e., "Fixed" and "Formula"), scaled by the volume of all trades. For firms that operate in more than one market, hedgability is the capacity-weighted average of the hedgability in each market in which the firm is active. Source: Own calcula- tions based on FERC's EQR data.
Hedgability (EQR,firm)	A firm's fraction of transactions that use market-based rates. The calculation follows Hedgability (EQR,region) with the exception that the data is aggre- gated on the firm-level instead of market-level. Source: Own calculations based on FERC's EQR data.
Other Variables	
Assets	Total assets in US\$. Source: Worldscope or Market Intellignce (for U.S. / Canada)
Cash flow	Earnings before interest, taxes, depreciation, and amortization / total assets.
Leverage	Total debt / (Total debt plus book value of equity).
GDP per capita	GDP per capita (in 2010 US\$) in a country and year. Source: Worldbank.
Market-to-book	Market capitalization / book value of common equity.
Capex	Capital expenditures / total assets.
Dividend (dummy) Inflation	Dummy variable which equals one if the firm pays a dividend.
Demand forecast vol	Yearly inflation rate in a country. Source: Worldbank. Standard deviation of hourly day-ahead demand forecasts, normalized by a market's average demand level. The demand forecast is the hourly day- ahead demand forecast of the market operator, as published by the U.S Energy Information Administration, which is available after 2015Q2. De- mand forecast volatility is calculated during a firm's fiscal quarter. For firms that operate in more than one market, demand forecast volatil- ity is the capacity-weighted average of the demand forecast volatility in each day-ahead market in which the firm is active. Source: EIA https://www.eia.gov/opendata/qb.php?category=2122627.
EP stringency	Environmental policy stringency indicator published by the OECD. We use the energy-sector indicator, which considers 12 different aspects (e.g., CO2 taxes, emission limits, or trading schemes). The index is published for all OECD countries (plus Brazil, China, India, Indonesia, Russia, and South Africa) between 1990 and 2015. We use the policy stringency indicator in the headquarter country of the energy utility. Source: OECD.
Market (dummy)	Dummy variable which equals one if a wholesale market for electricity exists in a region and year and zero otherwise. For firms operating in more than one region, we use the region with the highest capacity to define this variable. Source: hand-collected.

Variable	Description
Market share	Production capacity of a particular firm in its largest electricity market re
(capacity)	gion, scaled by the capacity of all plants located in the same electricity marke
	region. Source: Own calculations based on WEPP and Market Intelligence
	database.
Total LC	Total credit lines (mi134204) scaled by total assets (mi132264). Source
	Market Intelligence.
Used LC	Drawn credit lines (mi134205) scaled by total assets.
Total LC-to-cash	Total credit lines (mi134204) scaled by total credit lines plus cash holdings
Unused LC-to-cash	Total credit lines (mi134204) minus drawn credit lines (mi134205) scaled by
	unused credit lines plus cash holdings.
$Volatility_{zero}$	Standard deviation of hourly electricity prices, normalized by a market's
	average electricity price level; for regions without a wholesale market for
	electricity, this variable is set to zero.
$Volatility_{price}$	Standard deviation of hourly electricity prices.
$Volatility_{diff}$	Standard deviation of hourly electricity price changes.
$Volatility_{std.diff}$	Standard deviation of hourly electricity price changes, normalized by a mar
	ket's average electricity price level.
Volatility [coal price]	Standard deviation of coal prices during a calender year. Coal prices refe
	to the prices of steam coal for industrial customers in US\$ per ton. The
	frequency of prices is quarterly. Source: EIA for U.S. states and IEA fo
	other countries.
Volatility [gas price]	Standard deviation of gas prices during a calender year. Gas prices refer to
	the prices for industrial customers in US\$ per MWh. The frequency of prices
	is monthly for U.S. states and quarterly for other countries. Source: EIA fo
	U.S. states and IEA for other countries.

Definition of Variables - continued

Country	market	first year	Ν
Australia	AEMO_NSW	1999	157,796
Australia	AEMO_QLD	1999	157,796
Australia	AEMO_SA	1999	157,796
Australia	AEMO_TAS	2005	$101,\!939$
Australia	AEMO_VIC	1999	157,796
Australia	AEMO_WA	2007	90,000
Austria	EXAA	2002	129,922
Belgium	BELPEX	2007	$87,\!567$
Canada	AESO	2000	$148,\!632$
Canada	IESO	2002	$128,\!616$
Czech Rep.	OTE	2010	$60,\!617$
Estonia	NP_EE	2010	59,223
France	EPEX_F	2001	$132,\!178$
Germany	EPEX_D	2000	$145,\!049$
Hungary	HUPX	2010	$56,\!517$
India	IEX	2008	74,068
Ireland	SEMO	2008	78,801
Italy	GME	2004	111,780
Japan	JEPX	2005	102,912
Korea	KPX	2001	$137,\!376$
Latvia	NP_LV	2013	$31,\!438$
Lithuania	NP_LT	2012	39,813
Netherlands	APX_NL	1999	150,514
New Zealand	EMI	1999	157, 128
Poland	TGE	2000	$144,\!665$
Portugal	OMIE_PT	2007	83,319
Romania	OPCOM	2005	100,765
Russia	ATS	2009	70,415
Scandinavia	NORDPOOL	1999	157,299
Singapore	EMC	2003	122,736
Slovakia	OKTE	2010	61,368
Spain	OMIE_SP	1999	157,791
Switzerland	EPEX_CH	2006	88,166
U.K.	APX_UK	2003	121,077
United States	CAISO	2010	$61,\!392$
United States	ERCOT	2011	$52,\!608$
United States	ISONE	2003	121,320
United States	MISO	2006	$95,\!855$
United States	NYISO	2000	148,903
United States	PJM	1999	157,800
Total/Avg.		2004	4,872,650

Appendix B: Overview on Electricity Markets

This table presents an overview on the electricity markets. Reported are the first year for which data is available (the start year for the data collection is 1999) and the number of observations (N). The last year with data is 2016. Scandinavia covers Denmark, Finland, Norway, and Sweden.