Hedging, Liquidity, and Productivity*

Guojun Chen[†], Zhongjin Lu[‡], and Siddharth Vij[§]

October 2020

Abstract

We study the effects of liquidity and productivity on corporate hedging decisions using a comprehensive dataset of oil and gas producers. Over a longer sample period than prior literature, we discover that hedging intensity is positively correlated with unrealized hedging gains and output prices, but negatively with operating cash flows. These new empirical patterns together challenge existing risk management models as unrealized hedging gains represent an unexpected shock to internal liquidity, while both operating cash flows and output prices are positively related to productivity. Incorporating procyclical collateral capacity and production-dependent depreciation into existing models can explain our empirical findings.

Keywords: Corporate hedging, Financial constraints, Productivity, Collateral constraint, Procyclical collateral capacity, Production-dependent depreciation, Hedging capacity.
JEL Classifications: G23, G30, G32

*Scheduled for the American Finance Association 2021 annual meeting. We are grateful to David Pursell, John Rielly, Jay Wilson, and Jeff Wood for detailed discussions on hedging practice at oil and gas firms. We thank John Campbell, Hayne E. Leland, Jun-koo Kang, Jeff Netter, Annette Poulsen, Robert Resutek, Neng Wang, Hayong Yun and seminar participants at University of Georgia for helpful comments. We thank Sam Audino, Ny Nguyen Truc Bui, Nelson Lam, Chong Ying Lee, David Schumm, Yeap Hwei Yee, and Yeoh Kar Yan for excellent research support.

[†]Assistant Professor, Nanyang Business School, Nanyang Technological University, Singapore 639798; email gjchen@ntu.edu.sg.

[‡]Assistant Professor of Finance, Terry College of Business, University of Georgia, Athens, GA 30602; email zlu15@uga.edu.

[§]Assistant Professor of Finance, Terry College of Business, University of Georgia, Athens, GA 30602; email siddharth.vij@uga.edu.

Mainstream risk management theories suggest that financial condition and productivity are two main determinants of hedging policies; however, there is little consensus in the literature on how they affect hedging. Specifically, financial constraint-based risk management models (e.g. Froot et al. (1993); Bolton et al. (2011)) argue that financially distressed or constrained firms hedge more as they are effectively more risk averse, while models emphasizing collateral constraints (e.g. Rampini and Viswanathan (2010, 2013); Rampini et al. (2014), hereafter collateral-based theories) predict that constrained firms hedge less since they lack sufficient collateral to implement their desired hedges. These models also have opposite predictions on the hedging to productivity relation, with the financial constraint-based models predicting a positive relation while the collateral-based models predict the opposite. Empirically testing these competing predictions can further our understanding of prevalent corporate risk management behavior (Giambona et al. (2018)). However, existing studies are hamstrung by both the scarcity of hedging data and the difficulty in measuring financial condition and productivity.

We design our empirical strategy to tackle these challenges and study the effects of financial condition and productivity on hedging. We manually collect detailed information on hedging positions, production, and reserves for public independent oil and gas exploration and production (E&P) firms between 2002 and 2016.[1] This sample is ideal for testing theoretical predictions on hedging policies for the following reasons. First, there is a well-developed commodity derivative market for oil and gas, and thus these firms have the means to hedge their output price risk – their dominant business risk. Second, using our sample firms surmounts the empirical hurdles faced in quantifying firms' hedging positions. Firms can manage risks via operational methods and/or financial derivatives. The operational hedging is difficult to measure, and the notional positions of financial derivatives are not disclosed in general. Unlike integrated oil and gas producers, independent E&P firms in our

[1] This sample period is chosen because of hedging data availability. See Section 1 for more details.

sample do not have downstream business as operational hedges and rely predominantly on financial hedges. Additionally, these firms disclose detailed contract-level information about their financial hedges, so we can quantify their hedging positions accurately.[2] Third, as we discuss later, for our sample firms we can use changes in output price and unrealized hedging gains to proxy for unexpected shocks to productivity and financial condition, respectively, which are generally difficult to measure (Erickson and Whited (2000) and Farre-Mensa and Ljungqvist (2016)). Finally, since our sample firms are relatively homogeneous, the concern that omitted industry characteristics may drive the results is alleviated to a great extent. Thus our sample provides a rare opportunity to delineate the effects of productivity and financial condition on hedging.

We start by showing that common proxies of financial constraints do not have a statistically significant relation with hedging intensity. These proxies include dividend payer status, cash holdings, Altman Z-score (Altman (1968)), leverage ratios, and credit ratings. Our results suggest that the lack of strong empirical support for these hedging determinants in the existing literature is unlikely a statistical power issue. Such an insignificant relation can be due to the multifaceted nature of firms' hedging policies, as the mainstream theories of risk management argue that hedging is determined by two sets of state variables – financial condition (e.g., liquidity, leverage, and collateral value) and exogenous productivity (e.g., input and output prices). Since these empirical measures of financial constraints are affected by both financial condition and productivity, they are not ideal for teasing out the theoretical relations between hedging intensity and the two sets of state variables.

We then investigate the effects of unrealized hedging gains, operating cash flows, and

[2]Existing studies mostly rely on an indicator of whether firms use financial derivatives to study firms hedging policies. Guay and Kothari (2003) caution about using these studies to infer the economic magnitude of firms' hedging policies, as the notional positions of the hedgers' derivatives can be small relative to the firm size. Notable exceptions include Tufano (1996), Haushalter (2000), Jin and Jorion (2006), Rampini et al. (2014), Bakke et al. (2016), Gilje and Taillard (2017), and Rampini et al. (2020). These studies, like ours, focus on the firms' hedging policies at the intensive margin and thus differ from the empirical studies that use a dummy variable for derivative use.

output prices on hedging. Unrealized hedging gains (losses) are changes in fair value of outstanding derivative contracts. Existing literature has found no evidence that oil and gas firms have superior ability to predict price changes in the derivatives markets, thus unrealized hedging gains constitute a reasonable proxy for an exogenous shock to firms' liquidity. We also include operating cash flows in the regressor set because unrealized hedging gains and operating cash flows add up to operating income, which is found to be an important hedging determinant (Rampini et al. (2014)). Since operating cash flows are affected by firms' production choices and thus economically different from unrealized hedging gains, disentangling their effects on hedging offers new insights. Finally, similar to Rampini et al. (2014) and Gilje and Taillard (2016), we use changes in the aggregate commodity price as an proxy for exogenous shocks to the productivity of these oil and gas producers because increases in the aggregate commodity price lead to higher production and are exogenous to individual firms' production or hedging choices.

We find that hedging intensity is positively correlated with unrealized hedging gains. We also find that hedging intensity is negatively correlated with operating cash flows but positively with the output price. The positive relation between hedging intensity and unrealized hedging gains (our proxy for liquidity) corroborates the findings in Rampini et al. (2014, 2020) and is more consistent with the collateral-based models. The negative relation between hedging and operating cash flows may be consistent with collateral-based models' prediction if it indicates a negative relation between hedging and productivity. However, the positive relation between hedging intensity and output price suggests the hedging to productivity relation is actually positive. Therefore, these results together present a challenge to both strands of existing models.

To understand our three new empirical findings, we add procyclical collateral capacity and production-dependent depreciation (PDD) to the existing mainstream risk management models.[3] The procyclical collateral capacity captures the fact that, in the low productivity state, the collateral value of capital is low while the margin requirement for hedging is high, both leading to a tightening of the collateral constraint. The PDD means that producing more depreciates the capital faster. Specifically, for oil and gas producers, PDD refers to the fact that producing oil and gas depletes firms' oil and gas reserves.

The procyclical collateral capacity helps to explain the positive relation between hedging intensity and the output price. In existing collateral-based models such as Rampini and Viswanathan (2010, 2013); Rampini et al. (2014), firms borrow more to invest in the high productivity state, which crowds out hedging under the collateral constraint.[4] In contrast, the procyclical collateral capacity allows both borrowing and hedging to rise in the high-productivity state as the collateral capacity is also high. This explains the positive correlation between the output price (our proxy for productivity) and hedging intensity.

The PDD feature introduces an intertemporal trade-off between producing today versus producing tomorrow, which leads to a negative production to liquidity relation. When the current-period liquidity is low, and thus the financial constraint is more binding, the shadow price of current profits is higher relative to the present value of future profits. This induces a financially-constrained firm to produce more than it would in the financially unconstrained case. The negative production to liquidity relation, coupled with the same positive hedging to liquidity relation as in the collateral-based models, generate a negative relation between operating cash flow and hedging.

Our model generates new testable implications. First, our model predicts that hedging intensity will be more sensitive to output prices for firms with more price-sensitive collat-

[3]Our model integrates both strands of existing models. The hedging policy in our model is driven by desired hedging – how much a firm would like to hedge if there were no collateral constraint – emphasized in the financial constraint-based models and the hedging capacity – the maximum attainable hedge given the collateral constraint and the borrowing plan – emphasized in the collateral-based theories.

[4]Rampini and Viswanathan (2010) notice the possibility of a procyclical collateral value, but they did not discuss the effects of such procyclicality on hedging and related corporate policies.

eral. Empirically, the proved undeveloped oil reserves are more sensitive to oil prices than the proved developed oil reserves. Consistent with our model, the hedging to oil price relation is more positive for oil firms with relatively more proved undeveloped reserves. Second, our model predicts that production is a decreasing and convex function of liquidity. Empirically, we find supporting evidence that the correlation between production and Altman's Z-score is more negative when the Z-score is low. Finally, our model predicts that, given the output price level, production and investments are negatively correlated, because increasing production and decreasing investment have equivalent effects on reserve and liquidity. Using data on firm-product level investment in reserves, we confirm this model prediction.

This paper contributes to the literature along several dimensions. Our key empirical contribution is to document three economically significant patterns in firms' hedging intensities that help delineate the multifaceted nature of firms' hedging decisions. We show that neither the financial constraint-based models nor the collateral-based models offer a complete explanation of why hedging intensities correlate positively with output price and unrealized hedging gains, and negatively with operating cash flows.

The time series of our sample is significantly longer than existing studies on oil and gas producers' hedging policy. This allows us to control for unobserved time-invariant firm-specific heterogeneity and investigate the average pattern over both bull and bear periods of the oil and gas markets.[5] To our knowledge, the only empirical studies on firms' hedging intensity that employ a similarly long time series are Rampini et al. (2014) and Rampini et al. (2020), which test the relation between firms' net worth and hedging intensity using airlines and bank holding companies, respectively. Our empirical setting complements these two papers by studying independent oil and gas producers. Furthermore, while Rampini et al. (2020) use the difference-in-differences approach to control for the productivity effect

[5]For example, the oil price went up by 150% during the period between 2002 and 2007 and the oil price dropped by 80% during the period between 2014 and 2016. (See Figure 1.)

on hedging intensity, we directly investigate the relation between productivity and hedging intensity.

We also contribute to the theoretical literature by introducing two new realistic features into existing risk management models. Procyclical collateral capacity, or more broadly state-dependent capital prices, has been used to explain corporate debt capacity and corporate investment (e.g., Shleifer and Vishny (1992); Kiyotaki and Moore (1997); Benmelech et al. (2005); Fostel and Geanakoplos (2008); Chaney et al. (2012); Brunnermeier and Sannikov (2014)). We show that procyclicality of collateral capacity also leads to procyclical hedging capacity. PDD, or the units-of-production depreciation method in accounting, is widely used for depreciation of tangible assets such as equipment and depletable resources. However, the academic literature almost always assumes constant depreciation over time, which is independent of production choice. We show that PDD generates a new intertemporal trade-off and thus has important implications for modeling firms' risk management, production, and investment decisions.

The rest of the paper proceeds as follows: Section 1 describes the theoretical motivations, empirical design, and the construction of our sample. Section 2 evaluates the hedging determinants proposed by existing theories and our new empirical measures for liquidity and productivity. Section 3 presents our extension to existing models and Section 4 tests new model implications. Section 5 concludes.

1. Empirical Design and Data

1.1. Theoretical Motivation and Empirical Design

We motivate our empirical analysis by considering the mainstream risk management theories. As the seminal work of Modigliani and Miller (1958) points out, risk management, including hedging, is irrelevant in a frictionless economy. Starting from Froot et al. (1993), the financial constraint-based theories argue that financial frictions motivate hedging. Since a firm wants to avoid the distress costs and external financing costs in the low internal liquidity state, it hedges in order to transfer internal funds from high to low liquidity state. In such models, the key determinants of hedging are financial condition and productivity. When the financial condition is bad or the internal liquidity is low, a firm will hedge more. Productivity is just a static parameter in these models. The comparative statics of these models suggest that hedging is positively correlated with productivity, in general, since the costs of forgoing valuable investment opportunities are higher.

Another strand of theories, namely the collateral-based models (Rampini and Viswanathan (2010, 2013); Rampini et al. (2014)), add a collateral constraint to the financial constraint-based models. In such models, both borrowing and hedging require collateral, which can either be in the form of liquid internal funds or partially pledgeable assets. In these models, when a firm has low liquidity today, it wants to hedge more because their liquidity is likely to be low tomorrow. This is similar to what is observed in the financial constraint-based models. However, in the collateral-based model, the available collateral in this low liquidity state is also lower, which restricts the capacity to borrow and hedge, resulting in lower hedging. Furthermore, in an economy with persistent productivity, a higher current productivity predicts better future productivity, leading to higher investment and thus higher borrowing. Due to the limited collateral, higher borrowing crowds out the hedging, resulting in a negative relation between current productivity and hedging.[6]

Besides these aforementioned theories, since shareholders of levered firms have a call option-like payoff on the firm value, risk-shifting theories (e.g., Jensen and Meckling (1976))

[6]Besides these two strands, other theories of risk management emphasize the role of managerial risk aversion (Stulz (1984)), information asymmetries between managers and shareholders (DeMarzo and Duffie (1995) and Breeden and Viswanathan (2015)), conflict of interests between managers and shareholders (Bolton et al. (2019)), tax convexity (Graham and Smith (1999)), and the financial condition of the speculators in the derivative markets (Acharya et al. (2013)).

predict that shareholders have incentive to take more risks by hedging less and transferring the cost to creditors. Such risk-shifting (or asset substitution) effects are stronger when the firm is more financially distressed, which predicts a negative relation between financial constraints and hedging intensity. Since the distress cost effects (as in Smith and Stulz (1985) and Froot et al. (1993)) and the risk-shifting effects (as in Jensen and Meckling (1976)) predict opposite relations between financial constraints and hedging intensity, Purnanandam (2008) and Cheng and Milbradt (2012) argue for a non-monotonic relation between hedging and financial constraint.

In sum, the testable theoretical implications of these risk management models are:

1. Firms' financial condition and hedging intensities can be correlated negatively (Froot et al. (1993), Bolton et al. (2011)), positively (Rampini and Viswanathan (2010, 2013); Rampini et al. (2014)), or non-monotonically (Purnanandam (2008); Cheng and Milbradt (2012); Fehle and Tsyplakov (2005)).

2. Firms' productivity and their hedging intensities are negatively correlated when productivity shocks are persistent (Rampini and Viswanathan (2010, 2013); Rampini et al. (2014)).[7]

We design our empirical analyses to delineate the effect of two state variables, financial condition and productivity, on hedging as predicted by the standard models. Our key empirical strategy is to use the *unrealized* hedging gains as a shock to internal liquidity and the commodity price as a proxy for productivity. Unrealized hedging gains are mark-to-market profits on outstanding derivative contracts. We isolate unrealized hedging gains from the rest of operating income, because unrealized hedging gains are determined by unpredictable changes in commodity prices given the existing hedging positions, and thus not tied to firms'

[7] Bolton et al. (2019), which focus on the inalienability of risky human capital, also predict a positive relation between a persistent productivity shock and the hedging based on the limited commitment of risk-averse managers.

production plan.[8] In contrast, the rest of the operating income is tied to firm's production plan and partly predictable since a portion of the revenue is locked in via financial hedges. Therefore, we decompose the operating income before depreciation and amortization into two components: unrealized hedging gains and operating cash flows.

We want to emphasize that the realized hedging gains should be included in operating cash flows and, unlike unrealized hedging gains, are not used as a proxy for unexpected shock to internal liquidity. This is because realized hedging gains pertain to derivatives for current year production, whereas the unrealized gains pertain to derivatives hedging for future production. Since both the current year production and its corresponding hedging derivatives have offsetting exposures to the commodity price, the realized hedging gains caused by changes in commodity price will be offset by the corresponding changes in the unhedged revenue of the current year production. Therefore, the realized hedging gains have no net impact on the hedged revenue of the current year and thus do not constitute an unexpected shock to firms' liquidity position. In contrast, the unrealized hedging gains are, by definition, not offset by the unhedged revenue of the current year production, and thus do affect firms' liquidity position. Because the unrealized hedging gains are determined by existing hedging positions and unexpected changes in prices of commodity derivatives, they can be used as a proxy for changes in firms' liquidity position.[9]

To illustrate this point, we consider a firm that enters into forward contracts at the beginning of 2004 to sell 100 million barrels of crude oil equivalent (MMBOE) of its 2004 oil production and 50 MMBOE of its 2005 oil production. Assume that the forward prices

[8]We are not aware of any empirical evidence showing that these hedgers have superior ability in timing the commodity derivatives markets. In theory, risk-averse hedgers in equilibrium should pay the risk premium (Acharya et al. (2013)), which is also supported by the negative average unrealized gains in the summary statistics in Table 2.

[9]There is not much reason to believe that unrealized hedging gains are used by management to show better liquidity position at the end of the reporting period and are hence contaminated as a proxy for a shock to liquidity. In Table 2, the mean and median of unrealized hedging gains is nearly zero which is exactly what we would expect given its unpredictable nature. In regressions, we include firm fixed effects which control for any firm-specific factors that can affect unrealized hedging gains.

for the 2004 and 2005 contracts are the same at $50 per barrel of oil equivalent (BOE). For simplicity, further assume that the risk-free rate and the convenience yield are zero. Suppose the spot price is $50 per BOE at the beginning of 2004 and $40 at the end of 2004. So the realized gains on the 2004 contract and the unrealized gains on the 2005 contract are $1B and $500M, respectively. Three observations are in order. First, the changes in spot price throughout 2004 affect the realized gains/losses on the 2004 forward contract and thus affect the composition of the hedged revenue of 2004 oil production – whether it comes from the realized hedging gains or the unhedged revenue. However, the change in spot price does not affect the $5B revenue (100 MMBOE times $50 per BOE) for the 100 MMBOE of 2004 oil production. Second, the changes in spot price throughout 2004 affect the unrealized gains and losses on the 2005 forward contract, which in turn affect the firms' liquidity position. Third, if the spot price in 2005 does not change from the spot price at the end of 2004, the unrealized gains and losses of $500M on the 2005 forward contract at the end of 2004 will be reclassified as the realized gains and losses at the end of 2005. Thus, the realized gains and losses may not correlate with the contemporaneous changes in commodity prices.

We use the commodity price to capture exogenous shocks to firms' productivity. A high commodity price effectively induces oil and gas producers to produce morebecause it increases firms' marginal profitability.[10] The prices of oil and natural gas are exogenous because they are determined in global markets where the independent E&P firms in our sample are price-takers. Thus it is much more likely that our sample firms make production and hedging decisions given the commodity price than these firms try to manipulate the commodity price by changing their production and hedging policies. Nevertheless, we alleviate the concern regarding the exogeneity assumption of commodity price by employing the Kilian (2009) index as an instrument for commodity price. Kilian index uses the bulk

[10]Similarly, in Rampini et al. (2014), the effective productivity depends on both the total factor productivity and the commodity price, where the commodity price is the cost of an additional input in their model.

dry cargo shipping rates to capture global economic activity, which is widely used to proxy the aggregate demand for commodities in the literature studying the determinants of the real price of oil. Since an independent oil and gas producer is unlikely to affect the aggregate demand, this index is a valid instrument for the output price. Admittedly, we cannot completely rule out all potential omitted variables that simultaneously affect hedge ratios, liquidity, and productivity. However, all aforementioned risk management models have only two state variables, namely liquidity and productivity, and thus under the null hypotheses it suffices to test the effects of liquidity and productivity on the hedge ratio.

Our empirical design differs from the existing literature in several ways. First, existing empirical studies have not examined the relation between productivity and hedging, either because these studies have a short time series and are cross-sectional in nature, or because productivity is difficult to measure in their empirical setting. Using the commodity price as a proxy for productivity, we can directly examine the hedging to productivity relation. Second, to our knowledge, this paper is the first to study the relation between firms' liquidity position and hedging intensity by using the unrealized hedging gain as a proxy for shocks to firms' financial condition. We manually collect the unrealized hedging gain data directly from firms' 10-K filings by summing up both the unrealized gains and losses reported under the cash flow statements (for derivatives not designated as cash flow hedges), and the gains and losses reported under other comprehensive income (for derivatives designated as cash flow hedges).

1.2. Data

As we discuss in the introduction, we focus on oil and gas producers because they offer an ideal empirical setting to study corporate hedging policies. Our empirical setting is similar to that in several existing empirical studies on hedging, such as Haushalter (2000), Jin and Jorion (2006), Bakke et al. (2016), and Gilje and Taillard (2017); however, we expand the time series substantially.[11] We also exclude integrated oil and gas producers and focus on independent oil and gas exploration and production (E&P) firms, because the latter predominantly use financial derivatives to hedge the commodity price risk.[12]

We collect hedging data from 10-K filings of public independent oil and gas producers. The sample period is between 2002 and 2016 due to hedging data availability. The Financial Accounting Standards Board issued Statements of Financial Accounting Standards No. 133 (hereafter SFAS 133) in June 1998 to establish reporting standards for derivative instruments. Prior to SFAS 133, commodity related derivatives that have physical settlements are not required to be disclosed. After SFAS 133, firms are required to disclose all derivative positions on the balance sheet and the changes in their fair value in the income statement or shareholders' equity, including the ones used for hedging activities.[13] All of our sample companies adopted this standard by 2002.

It is important to note that even after SFAS 133, firms are still not required to disclose the notional volume, instrument types, and maturity, which are indispensable for quantifying firms' hedging positions. Such information is not part of the required disclosure because such information can reveal a firm's cost structure to its competitors if the hedging pertains to the input price. This is not a concern for independent oil and gas producers in our sample because the hedging pertains to the output price. Thus we are able to find detailed information regarding the notional volume, instrument types, and maturity for all firms in

[11]Besides oil and gas producers, prior empirical studies also investigate other industries. For example, Tufano (1996) studies gold mining companies with limited information on hedging from survey data. Rampini et al. (2014) focus on airline companies, and Bonaimé et al. (2014) and Rampini et al. (2020) on financial institutions.

[12]We exclude integrated oil and gas producers becausue their refinery segments use oil and gas as the inputs and thus provides a natural operational hedge for the exploration and production segment, which significantly reduces the need to hedge using financial instruments.

[13]Although firms are required to disclose the face value, contract types, or notional amount of financial instruments with off-balance-sheet risk of accounting loss starting from SFAS 105 in 1990, commodity and other derivatives that involve physical settlement were exempted from disclosure requirements until the implementation of SFAS 133. As a result, early empirical studies on hedging policies have to rely on data from surveys and voluntary disclosures.

our sample.

Appendix A describes the data collecting process in detail. We also collect financial data from Compustat and gather more information on product-level production, proved reserves, and firm-level breakdown of changes in proved reserves from Bloomberg. We obtain the futures price for the front month contract for West Texas Intermediate (WTI) crude oil, and Henry Hub natural gas from the U.S. Energy Information Administration. Table 1 reports how we define and construct our key empirical variables.

Table 2 presents summary statistics on our final sample. The median hedge ratio is 0.484, which is significantly higher than the ratio found in prior studies (Haushalter (2000); Jin and Jorion (2006)). This is a result of our filtering process that excludes integrated oil and gas producers. As a result of this exclusion, fewer than 5% of firm-years in our sample have a hedge ratio equal to zero. The median book asset value is $2.3 billion. These companies are profitable with a median operating profitability of 14.8%. At the same time, the median cash holding of these companies is only 1.4%, the book leverage is 31.3%, and a dividend is paid in about 56% of all observations. These numbers suggest that, compared to other public firms in the U.S., oil and gas producers are more levered and save relatively little in cash. Therefore, our findings may not apply to financially flexible firms with ample liquidity.

2. Hedging Determinants

In this section, we implement our empirical design and evaluate the effects of potential determinants of corporate hedging. We first evaluate several proxies of financial condition examined in the literature. Then we use our new empirical measures to investigate the effects of internal liquidity and productivity on corporate hedging.

Following Haushalter (2000), we estimate the following ordinary least squares multivariate regression using our panel data:

$$HedgeRatio_{i,t+1} = \alpha + \beta X_{it} + \gamma_i + \delta_t + \varepsilon_{it} \, .$$

The dependent variable of interest, the *HedgeRatio*, is the firm i's hedging position for year $t+1$ reported at the end of year t, scaled by year t production.[14] X_{it} is a vector of independent variables of interest that are predicted to influence hedging intensity. γ_i and δ_t are firm and year fixed effects. We compute standard errors that are clustered at both the year and firm levels.

2.1. Hedging and Financial Condition

Table 3 presents the estimation results with the regressors being extant proxies of financial condition and profitability. In Column (1), we include no fixed effects. In Columns (2) and (3), we include year and firm fixed effects respectively. In Column (4), both year and firm fixed effects are included. This ability to add firm fixed effects, due to our long time series, differentiates our analysis from existing empirical studies on oil and gas firms' hedging policies.

In Panel A of Table 3, our regressors include the following commonly used empirical measures related to financial condition: (i) whether the firm pays dividends; (ii) the firm's credit rating, if it has one; (iii) the firm's size measured by the log of book assets; (iv) the firms' cash holdings divided by its total assets; (v) Altman Z-score (Altman (1968)); and (vi) book leverage. Financial distress is typically considered to be decreasing in the first five measures and increasing with the last measure. As discussed earlier, financial constraint-based theories predict hedging intensity to be positively correlated with financial distress, and

[14]By examining hedging positions in quarterly filings, we do not find evidence for window dressing that firms report artificially higher or lower *HedgeRatio* at the fiscal year end. In unreported results, we also find that the stock prices of firms with higher *HedgeRatio* indeed have a low sensitivity to the changes in commodity price.

collateral-based theories predict the opposite patterns, while Fehle and Tsyplakov (2005), Purnanandam (2008), and Cheng and Milbradt (2012) predict a non-monotonic relation.

We find that none of these financial condition measures are significantly correlated with hedging intensity at any conventional level across our four specifications. The existing empirical literature has documented mixed results on the relation between financial constraints and hedging intensity. Haushalter (2000) and Gilje and Taillard (2017) present evidence of hedging intensity increasing with leverage, while Adam and Fernando (2006) show that hedging intensity decreases with cash holdings. In contrast, Purnanandam (2008) finds evidence supporting a non-monotonic relation between financial constraints and hedging intensity. Our results contribute to this growing literature by showing that the relation is not significantly different from zero when evaluated over a substantially longer time series.[15]

Next, we test the relation between profitability and hedging. We follow the literature and use return on assets (ROA) as the empirical proxy for profitability. We do not find a significant relation between ROA and hedging intensity in our multivariate regressions. We revisit this finding in depth in the next subsection.

Third, we investigate the relation between hedging intensity and investment, which is affected by both liquidity and productivity channels. In Panel A of Table 3 we find a statistically insignificant relation between hedging intensity and investment when including the firm and year fixed effects. We use the ratio of capital expenditure over assets as a proxy for investment. Since higher investments can indicate higher liquidity and better investment opportunities, we also use Tobin's Q to more specifically measure investment opportunities. We find that the relation between hedging intensity and Tobin's Q is also statistically insignificant. Our findings reinforce the inconclusive results reported in the existing empirical

[15]We cannot completely rule out the usual errors-in-variables concern that the measurement errors in these empirical measures bias the regression coefficients towards zero; however, the use of multiple proxies ameliorates this concern to a great extent. To rule out multicollinearity concerns, in unreported univariate regressions, we also examine each one of the financial constraint measures at a time. We find that none of the measures have a significant relation with hedging intensity once we include time and year fixed effects.

studies, which are based on shorter sample periods. For example, Haushalter (2000) find a positive and significant correlation between hedging intensity and capital expenditure, whereas Carter et al. (2006) find the correlation to be insignificant. Allayannis and Weston (2001) and Carter et al. (2006) find a positive relation between hedging intensity and Tobin's Q while Adam and Fernando (2006) find a negative one.

Finally, we find that including the firm fixed effects substantially increases the R^2 of the multivariate regression. The R^2 is 0.032 in Column (1) without fixed effects, and 0.522 in Column (3) with the firm fixed effects. This suggests that the time-invariant firm characteristics play a significant role in determining hedging, as well as other firm policies. As a result, we control for these characteristics by including firm fixed effects in the following regressions.

2.2. Hedging and New Measures of Liquidity and Productivity

In this subsection, we use the unrealized hedging gains as a shock to internal liquidity, and the commodity price as a proxy for the productivity, to delineate the effects of financial condition and productivity on hedging.

The standard measures of profitability used in the literature, such as net income or operating income, contain two economically distinct sources of income. The first component, the (hedged) operating cash flows generated by the current-year production, pertains to a firm's operational efficiency, which to a great extent is determined by the firm at the beginning of a fiscal year (if the firm chooses to lock in its revenue using hedging derivatives). The second component, the unrealized gains and losses on derivatives used to hedge future production, reflects the outcome of a firm's risk management decisions that are largely driven by unpredictable changes in commodity price. From the summary statistics, we can see that standard deviation in unrealized hedging gains and losses is over half that of operating income. This is because a substantial portion of E&P firms' revenue is protected by hedging derivatives, and thus unrealized hedging gains and losses are economically meaningful shocks to E&P firms' financial condition.

Therefore, we separate the unrealized gains from (existing) hedging positions from the rest of the operating income – proxied by operating cash flows – and investigate their respective effects on hedging intensity in Table 4. In Column (1) with firm fixed effects, we see that operating cash flows have a negative correlation with hedging intensity that is statistically significant at the 5% level, while the unrealized gains/losses on existing hedging positions have a positive correlation with hedging intensity with a 10% statistical significance. The positive relation between the unrealized hedging gains - our proxy for shocks to liquidity - and hedging intensity is consistent with the theoretical prediction of the collateral-constraint models. These models also predict a negative correlation between hedging and productivity because high expected productivity induce firms to invest, leading to higher borrowing and a reduced hedging position under the collateral constraint. If this prediction is true and operating cash flows correspond to productivity, then we should observe a negative relation between hedging and operating cash flows in the data.

To investigate the relation between hedging and productivity, Column (2) of Table 4 adds the commodity price, a direct proxy for oil and gas firms' productivity, to the regressor set. Since many E&P firms produce both oil and gas, we use the production-weighted average of the front month futures prices for both WTI (West Texas Intermediate) oil futures and Henry Hub natural gas futures at the fiscal-year end. We find that after controlling for the commodity price, the coefficients on both operating cash flows and hedging gains/losses retain the same signs and become larger in magnitude. These coefficients are now significant at the 1% and 5% levels, respectively, indicating that the opposite effects of operating cash flows and hedging gains/losses on hedging intensity are robust to controlling for the commodity prices. Furthermore, we find that the regression coefficient on the commodity price is positive and highly statistically significant. In Figure 1, we plot the cross-sectional median hedge ratio against the price, separately for oil and natural gas over our sample period. We find that the positive relation is particularly strong for the crude oil, consistent with the notion that the crude oil markets are more integrated and the prices in different regions are less affected by the local factors as compared to natural gas.[16] Our results thus indicate a positive hedging-productivity relation, which cannot explain the negative relation between hedging and operating cash flows documented in Column (2). In Columns (3) and (4) of Table 4, we conduct robustness tests by adding the set of control variables used in Almeida et al. (2019). The controls are sales/assets, log assets, and the market-to-book ratio. Adding these controls does not qualitatively change the results.

In addition to statistical significance, our key explanatory variables also have an economically significant impact on hedging. For example, with the control variables in Column (4), a one standard deviation rise in operating cash flows leads to about a four percentage point decrease in the hedge ratio; and a one standard deviation rise in unrealized hedging gains increases the hedge ratio by three percentage points. The output price is the most important one, as a one standard deviation rise in the log production-weighted price increases the hedge ratio by seven percentage points. Relative to a median hedge ratio of 0.48, our regressors are important in explaining the corporate hedging policies.

Another potential explanation for the positive relations between the hedging intensity and the output price or the liquidity is risk-shifting (Jensen and Meckling (1976) and ?). Under this explanation, when the output price is low or the internal liquidity is low, financially distressed firms have an incentive to take more risks by hedging less. This can generate the positive hedging to price or hedging to liquidity relation that we document in Table 4. To examine this explanation, we run a robustness test in which we exclude the most distressed firms by filtering out the bottom 10% of firm-year observations based on Altman Z-Score.

[16] For the point that natural gas markets are more regionalized than crude oil markets, see this report "Natural gas markets remain regionalized compared with oil markets."

The results in Table X1 show that the magnitude and statistical significance of the key variables are very similar to our results in Table 4. The coefficients on operating cash flows and hedging gains/losses are negatively and positively significant at the 1% and 5% levels, respectively. The coefficient on the price variable is significant at the 5% level. These results provide evidence that risk-shifting is unlikely to account for our results.[17]

As discussed in Section 1.1, we alleviate the concern regarding the exogeneity assumption of commodity price by employing the Kilian (2009) index as an instrument for commodity price. Results from the instrumental variable analysis are presented in Table X2. Columns (1) and (2) are analogous to the reduced-form results in Columns (2) and (4) of Table 4, respectively. The coefficient on the instrumented price variable is very close to that in the reduced-form analysis, and is statistically significant at the 5% level. In fact, the coefficients on the other variables in this instrumental variable analysis are also very similar to those in the reduced-form analysis. The F-statistic of near 10 suggests the instrument is not weak. Together, these results suggest that neither reverse causality nor an omitted variable is likely to drive the relation we document between hedging and the commodity price.

Taken together, our empirical findings are intriguing. First, the strong positive correlation between unrealized hedging gains and the hedging intensity is consistent with the positive relation between liquidity and hedging in the collateral-based models (Rampini and Viswanathan (2010, 2013); Rampini et al. (2014)). Second, if we consider operating cash flows as a proxy for productivity, then the negative relation between operating cash flows and hedging corresponds to the negative hedging-productivity relation in the collateral-based models. However, the positive hedging to output price relation challenges this interpretation. As a result of the opposite relations of hedging intensity with both operating cash flows and

[17] Consistent with our findings, Rampini et al. (2014) and Rampini et al. (2020) find the positive relation between hedging intensity and net worth is robust to removing distressed firms in different industries. Andrade and Kaplan (1998) finds no evidence of risk-shifting; and Rauh (2009) suggests that financial distress consideration outweighs the risk-shifting incentives. In the oil and gas industry, Gilje (2016) finds that firms reduce instead of increase risk-taking when they approach distress.

output prices, in the next section we explore the role of firms' production..

To the best of our knowledge, our findings are the first to document a significant relation between commodity price and hedging intensity among independent oil and gas E&P companies. Based on our conversations with executives at three major firms in the industry, the aggregate commodity price is a major determinant in their hedging decision making process.[18] However, although price movements can be viewed as productivity shocks in the workhorse models of risk management, existing empirical studies have not investigated the relation between price and hedging intensity. This is probably because most existing empirical studies have short time-series data, and thus can only study the cross-sectional relation. In contrast, our panel data with a longer time series than in the existing literature enable us to examine the relation between hedging intensity and price.

3. Model

This section presents a model to reconcile our new empirical findings. The model nests the two strands of risk management models and extends these models by introducing two new elements: (1) a collateral constraint with procyclical collateral capacity and (2) production-dependent depreciation (PDD).[19] The nesting helps us to distinguish the key mechanisms of these models. Specifically, we show that the optimal hedging policy is jointly determined by desired hedging and hedging capacity, the key results of the financial constraint-based models and the collateral-based models, respectively. The two new elements are crucial in reconciling our three new empirical findings.

[18] Because the hedging policy is determined by other factors and different firms use the prevailing price differently, these conversations do not indicate a clear linear relation between price and hedging intensity.

[19] The PDD corresponds to a common depreciation method in practice called units-of-production method, which is widely adopted in our sample firms. For example, in its 2007 Annual Report, Apache stated: "Apache's Depreciation, Depletion and Amortization (DD&A) of oil and gas properties is calculated using the Units of Production Method (UOP). The UOP calculation in simplest terms multiplies the percentage of estimated proved reserves produced each quarter times the costs of those reserves." See Appendix C for an example of how the production affects the reserve for oil and gas exploration and production firms.

3.1. Model Setup

State and price dynamic In a dynamic economy, a risk-neutral oil or gas producer is a price taker and its output price follows a two-state Markov chain: $P_t \in \{P_-, P_+\}$, where $P_+ > P_-$. The transition probabilities are:

$$\begin{bmatrix} 1-\pi_- & \pi_- \\ \pi_+ & 1-\pi_+ \end{bmatrix}.$$

Here, π_s, $s \in \{-,+\}$, is the probability of current state s transitioning to a different state in the next period. Under this assumption, the expected future output prices conditional on the current state s is:

$$\overline{P}_s \equiv (1-\pi_s)\, P_s + \pi_s P_{s-}\,.$$

To explain our findings, we calibrate $\pi_- = \pi_+ = 0.2$. This generates an annual autocorrelation of 0.6 for the price process, which matches the estimated autocorrelation of oil prices during our sample period. So the price process is persistent and $P_+ > \overline{P}_+ > \overline{P}_- > P_-$.

Real decisions: production and investment Given the current state s and the capital K, a firm chooses its time-t production volume Z_t. The operating profits are the revenue $P_t Z_t$ minus a convex production cost $\frac{\gamma}{2} Z_t^2 / K_t$:

$$\Pi\,(Z_t, P_t, K_t) \equiv P_t Z_t - \frac{\gamma}{2}\frac{Z_t^2}{K_t}\,. \tag{1}$$

The capital K_t is the oil and gas reserves in barrel of oil equivalent (BOEs) at time t, which follows the dynamic:

$$K_{t+1} = (1-\delta)\, K_t + I_t - Z_t\,. \tag{2}$$

Here, δ is the depreciation rate. I_t is the capital investment on reserves. Investment costs include both a linear adjustment cost $\phi_1 I_t$ and a convex adjustment cost $\frac{\phi_2}{2} I_t^2 / K_t$, both in the unit of dollars, as follows,

$$\Phi\left(I_t, K_t\right) = \phi_1 I_t + \frac{\phi_2}{2} I_t^2 / K_t.$$

A key innovation of our model is the last term, production Z_t, on the right side of equation (2), which captures the *production-dependent depreciation* (PDD): the higher the production, the more capital is depreciated. This is motivated by the fact that reserves are limited resources, and the more an oil or gas firm produces, the faster the reserves are depleted. See Appendix C for a real-world example.[20]

With PDD, our model features a new intertemporal trade-off in a firm's production plans. Holding other corporate policies unchanged, higher production today depreciates the capital faster, leading to lower production in the future. As we will show later, this new intertemporal trade-off interacts with the financial constraint, which helps to explain our new empirical findings. In contrast, in traditional models, production does not affect the capital dynamics and firms face only a contemporaneous static optimization problem. As a result, in these models firms' production decision is solely determined by the current productivity and not affected by the shadow price of current liquidity relative to future profits.

Financial decisions: hedging and borrowing The firm also chooses the hedging position for the next period, denoted by H_{t+1} (in BOEs). For simplicity, we assume the firm takes a short position in oil or gas forward contracts when hedging. The hedging gains or

[20]It should be noted that the notion of production-dependent depreciation applies far more widely than just the oil and gas industry. For example, an Uber driver makes living on his car. The more he drives, the more output he generates and the faster his car get depreciated. In accounting parlance, this is known as units of production depreciation, and is one of the four most popular depreciation methods for small and medium enterprises

losses at time $t+1$ depend on the difference between the delivery price agreed at time t, and the realized spot price at time $t+1$. Using no-arbitrage pricing, the delivery price of the forward is $\overline{P}_s$. So the hedging gain or loss realized at time $t+1$ is:

$$\Pi^H_{t+1}\left(H_{t+1}\right) = \left(\overline{P}_{s,t} - P_{t+1}\right) H_{t+1} \,. \tag{3}$$

Given that the price follows a two-state Markov chain in our model, when the future spot price P_{t+1} is low (i.e., $P_{t+1} = P_-$), the hedging position H_{t+1} will be profitable and thus protects the firm in the low-price state. Conversely, when price P_{t+1} is high (i.e., $P_{t+1} = P_+$), the hedging position suffers losses in this high-price state. In this sense, hedging enables intra-temporal smoothing for the future states.

The firm is financially constrained and can only borrow risk-free debt.[21] The net debt (debt minus cash) at the beginning of period t is denoted as B_t,[22] which has an interest rate r^B. When $B > 0$, the firm has positive net borrowing, and r^B is equal to the risk-free rate r. When $B < 0$, the firm has net savings, and r^B is less than risk-free rate.[23] Net debt's dynamics resembles a typical statement of cash flow:

$$B_t - B_{t+1} = \underbrace{\Pi_t}_{\text{oper CF}} \underbrace{-\Phi\left(I_t, K_t\right)}_{\text{inv CF}} \underbrace{-D_t - r^B B_t}_{\text{fin CF}} + \underbrace{\Pi^H_t\left(H_t\right)}_{\text{hedging gains}} \,. \tag{4}$$

[21]This assumption is equivalent to an environment where a firm faces infinitely high financing costs when raising risky debt or new external equity. This assumption simplifies our analysis and highlights the role of collateral constraint. Also, Fostel and Geanakoplos (2015) show that in a binomial economy, any equilibrium with default is equivalent to another no-default equilibrium.

[22]In our sample firms, average cash savings are only 3% while the book leverage is in the range of 20%-40% of total assets. So we focus on the net debt.

[23]The assumption that the interest rate on the net debt is lower than the risk-free rate when B_t is negative is used to generate equity payout when firms are not financially constrained. If the return on internal savings is the same as the risk-free rate, the firm will never payout. See Riddick and Whited (2009) and Bolton et al. (2011) for more detailed explanations.

Here, D_t is dividend, which is restricted to be non-negative due to limited liability:

$$D_t \geq 0 \,. \tag{5}$$

The (negative) change in net debt is equal to the sum of operating cash flow, investing cash flow, financing cash flow, and the hedging gains, as labeled below the respective terms in (4). Another way to interpret equation (4) is that, the difference between cash inflows and outflows on the right-hand side of the equation is equal to the negative change in the net debt account on the left-hand side.

A collateral constraint with procyclical capacity As in Rampini and Viswanathan (2010) and Rampini and Viswanathan (2013), the firm has a limited ability to pledge its future cash flows to secure the payment to its creditors and hedging counterparties.[24] Therefore, a firm's financing and hedging decisions are limited by the collateral value of the capital as below,

$$\eta_s K_{t+1} \geq \left(1 + r^B\right) B_{t+1} + \sigma_s H_{t+1} \,. \tag{6}$$

Our specification of the collateral constraint in (6) extends that in Rampini and Viswanathan (2010) and Rampini and Viswanathan (2013) in two ways. First, the collateral value per unit of capital (η_s) is state-dependent. In our model, we assume that this collateral value of capital is procyclical, i.e., $\eta_+ > \eta_- > 0$, to capture the fact that the dollar value per BOE reserve increases linearly in oil price.[25] This is consistent with the notion that capital goods have lower market liquidity in bad times (Shleifer and Vishny (1992); Kiyotaki and Moore (1997); Fostel and Geanakoplos (2008); Brunnermeier and Sannikov (2014)).

[24] As Rampini and Viswanathan (2010) point out, such collateral constraints can be derived endogenously from limited commitment models such as Kehoe and Levine (1993) and Kocherlakota (1996).

[25] η_s corresponds to $\theta q\left(s^t\right)$ in Rampini and Viswanathan (2010), the resale discount θ multiplying the price of capital q. Rampini and Viswanathan (2010) pointed out the possibility of procyclical collateral value, but they did not discuss the effects of such procyclicality on hedging and related corporate policies.

Second, σ_s, the margin requirement or the amount of collateral tied up by the hedging position, is also state-dependent. We assume that σ_s is the maximum loss per BOE hedging position, which is:

$$\sigma_s \equiv \max_{s_{t+1}} \left[P\left(s_{t+1}\right) - \overline{P}_s \right] = P_+ - \overline{P}_s \,. \tag{7}$$

Because of price persistence, $\overline{P}_+ > \overline{P}_-$ and thus $\sigma_+ < \sigma_-$. That is, the maximum loss possible is higher when the current price is low. This specification captures the idea that the hedging counterparties require the firm to put down sufficient collateral to protect their claims, even in the worst scenario when the firm suffers the maximum loss.

The collateral constraint (6) captures the important fact that both borrowing and hedging require collateral. The collateral constraint for borrowing is widely recognized in the academic literature. In reality, a firm posts collateral to decrease its financing costs.[26] In the model, we follow the literature and make the simplifying assumption that all borrowing is fully secured by the collateral, and therefore the borrowing is risk free. Hedging competes with borrowing for collateral because the derivative counterparties enjoy "effective seniority" relative to debt claims in bankruptcy under U.S. bankruptcy law (Bolton and Oehmke (2015)). Thus the collateral available for creditors is the total collateral minus that owed to the hedging counterparties.

Although a firm will never default on its debt and hedging contracts under the collateral constraint, firms still incur the distress costs in our model because when a firm's liquidity position is low, firms are forced to either forgo their positive net present value investment opportunities or liquidate their capital, both of which are costly.

[26]For example, firms use reserves as collateral in reserve-based lending, which has been widely seen in the U.S. energy sector during the past several decades. (See Azar (2017).)

A firm's problem At date t, the firm solves the following problem:

$$V\left(K_t, B_t, H_t, s_t\right) \equiv \max_{K_{t+1}, H_{t+1}, B_{t+1}, Z_t, I_t} E\left(\frac{1}{\left(1+r\right)^t} \sum_{t=0}^{T} D_t\right) \tag{8}$$

s.t. (2), (4), (5), and (6).

In this problem, at each date t, a firm is maximizing its shareholders' discounted cash flows V given four state variables, the beginning-of-period capital stock K_t, the beginning-of-period debt B_t, the hedging position H_t, and an exogenous state s_t. It has four choice variables, the hedging for next-period production H_{t+1}, the end-of-period debt B_{t+1}, the current production Z_t, and the current investment I_t.

To simplify the problem, we assume the firm operates for three dates only, i.e., $t = 1, 2, 3$.[27] At date 3, the firm is liquidated with the unit liquidation value of reserves being κ_s. This captures a reduced-form continuation value of the firm at date 3. Under this assumption of liquidation without production, the debt and hedging positions at date 3 are both zero, i.e, $B_3 = H_3 = 0$.

Furthermore, the whole problem is homogeneous of degree one with respect to (K_t, B_t, H_t). We thus scale all variables by K_t and denote them by their corresponding lower cases, such as $h_t \equiv H_t/K_t$ and $b_t \equiv B_t/K_t$. Without loss of generality, we further assume $K_1 = 1$.

Finally, the two state variables b_t and h_t can be summarized by one single state variable w_t, which is the net liquidity:

$$w_{t+1}\left(s_{t+1}\right) \equiv -\left(1+r_B\right) b_{t+1} + \left[P\left(s_{t+1}\right) - \overline{P}_s\right] h_{t+1}\,. \tag{9}$$

The problem is further simplified to one with only one continuous state variable w, which summarizes a firm's financial condition, and one binary state variable s, which captures the

[27]For a more general treatment with infinite periods, please refer to the Appendix.

productivity state. So the value function becomes $v(w_t, s)$. See the Appendix for more information about the derivation.

3.2. Solutions and Interpretation

In this subsection, we solve the model and summarize the implications in Figures 2 and 3. Here, we present the key predictions and explain the corresponding intuitions. Detailed proofs and the model parameters are presented in Appendix E.

Policy functions (except for hedging) We first present the policy functions of our model in Figure 2, except for the hedging policy. The x-axis is the current net liquidity w_1. The two lines are the two policy functions in different price states: the blue solid line is for the high-price state ($s = +$) and the red dashed line is for the low-price state ($s = -$).

Panel (a) shows that the investment policy i_1 is increasing in both the current liquidity and the output price. The mechanisms are very similar to that in the neoclassical models of investment. First, when the current net liquidity is high, the firm is less financially constrained and thus can invest more. Second, when the current output price is high, the expected future output price is also high as the price process is persistent. The high current output price also means high current operating profits and thus more liquidity. Both a higher expected future output price and more liquidity lead to higher investment. Moreover, the investment sensitivity to price is increasing in liquidity, that is, the difference in investment across states is increasing in liquidity, because the marginal value of cash (MVC) is lower when liquidity is high and thus the investment becomes more responsive to output price.

Panel (b) shows the production policy z_1. z_1 is increasing in the current output price P_1 because a higher output price implies a higher marginal benefit of production and thus firms have incentives to produce more. z_1 is decreasing in the current liquidity w_1, because when w_1 is low, the financial constraint is more binding, and it is more valuable to generate cash flows now than in the future.

Production z_t plays a more interesting role in our model with the PDD feature than in standard models. As we discussed before, producing today reduces production tomorrow. This intertemporal trade-off interacts with the tightness of the financial constraint. When the current-period financial constraint is more binding, the shadow price of current profits is higher relative to the future value of production. Consequently, low current internal funds can force a financially constrained firm to produce more than the optimal level under the unconstrained case. In contrast, in the existing models such as Froot et al. (1993), Rampini and Viswanathan (2010), and Bolton et al. (2011), the production is determined by the exogenous productivity and independent of a firm's liquidity position. As we discuss below, this PDD channel helps our model match the empirical patterns better than the existing models.

Panel (c) shows that b_2 is increasing in P_1 but decreasing in w_1. When the output price P_1 is high, both production and investment are high. The former leads to a higher operating profit and the latter leads to a higher investment cash outflow. With PDD, investment responds more to the increase in P_1 than production does. Therefore, the increase in the investment cash outflow outpaces the increase in the operating profit, which requires more borrowings (a higher b_2). Additionally, due to the procyclical collateral value, a firm has a higher debt capacity in the high-price state. As a result, not only does the firm want to borrow more during the high-price state, because of the investment need, but it is also able to do so. b_2 is decreasing over the current net liquidity w_1, because ceteris paribus, a higher liquidity means the firm borrows less to execute the same production and investment plans.

Panel (d) plots the marginal value of cash (MVC). The MVC is always greater or equal to 1, indicating that in our model, firms are financially constrained and value internal liquidity more than external liquidity. The MVC is decreasing in liquidity w_1, implying that the value function is concave in liquidity. This implies that risk-neutral firms exhibit endogenous aversion to uncertain shocks to cash in our model, similar to standard models with financial frictions such as Bolton et al. (2011). Finally, the difference in MVC between high-price and low-price states is decreasing in liquidity w_1.

Hedging policy Figure 3 presents the hedging policy, the main variable of interest in this paper, and its decomposition.

Panel (a) plots the optimal hedging, h_2. First, hedging is higher in the high-price state than that in the low-price state. Second, hedging in the high-price state exhibits a strong nonlinear pattern. When the liquidity is low, hedging is increasing over liquidity, which is consistent with Rampini and Viswanathan (2010, 2013). When the liquidity is higher, hedging becomes decreasing and locally convex, which is consistent with Froot et al. (1993) and Bolton et al. (2011). To understand such patterns, we decompose the optimal hedging into the following two parts.

Panel (b) plots the desired hedging, which is defined as the optimal hedging as if the collateral constraint were not binding at the end of period 1.[28] Without a binding collateral constraint, given the optimal intertemporal smoothing decisions involving investment, production, and borrowing decisions, a manager would choose a hedging policy that equates the MVC in the future low-price and high-price states:

$$\frac{\partial v_2\left(w_2^+,+\right)}{\partial w_2} = \frac{\partial v_2\left(w_2^-,-\right)}{\partial w_2}. \tag{10}$$

In general, a lower current liquidity w_1 will lead to lower future liquidities in both states (w_2^+ and w_2^-). The low future liquidity results in a larger gap in MVC between the future high- and low-price states, as shown in Panel (d) of Figure 2. Thus, a higher level of hedging is needed to equate the MVCs between the two states. This explains why a lower current

[28]We construct the desired hedging and the maximum hedging after deriving optimal investment, production, and borrowing.

liquidity leads to a higher desired hedging, as shown in Panel (b). This negative relation between the current liquidity and hedging is similar to workhorse models without collateral constraints such as Bolton et al. (2011).

In Panel (b), we also find that the desired hedging is lower in high-price state when liquidity is low but this gap narrows when liquidity is high. This phenomenon is a result of two competing forces. On the one hand, a firm in a high productivity state can generate more operating cash flows, which increase the firm's liquidity position. This lowers the desire to hedge. On the other hand, due to the persistence in output prices, a higher current price implies a higher average future price. This encourages higher investments, which reduce the firm's liquidity position. This increases the desire to hedge. When the liquidity is low, investments are less responsive to changes in output prices and thus the operating cash flow channel dominates, resulting in a negative correlation between the desired hedging and output price. When the liquidity is high, the investment channel becomes more important, reducing the negative correlation between the desired hedging and output price.

Panel (c) presents the hedging capacity, the maximum attainable hedging a firm can achieve given the collateral constraint:

$$\overline{h}_2\left(s\right) = \frac{\eta_s - \left(1 + r_B\right) b_2\left(s\right)}{\sigma_s}\,, \tag{11}$$

where $s \in \{+, -\}$ is the price state at date 1. Given a price state s, the hedging capacity is negatively correlated with borrowing b_2 and thus the liquidity, because hedging and borrowing compete for the collateral. The hedging capacity is higher in the high-price state. This is due to the effects of the collateral value per BOE reserve,η_s,and the margin requirement per BOE hedging, σ_s, in (11): η_s is higher in high-price state and σ_s is lower in the high-price state. Both forces work in the same direction and result in a higher hedging capacity in the high-price state.[29]

Together, Panels (b) and (c) of Figure 3 help illustrate the mechanisms underlying the optimal hedging in Panel (a) of Figure 3. The optimal hedging is the minimum of the desired hedging and the hedging capacity. The asterisk (*) denotes the cutoff point where the desired hedging and the hedging capacity cross each other. In the low productivity state ($s = -$, red dashed curves), the desired hedging always exceeds the hedging capacity, so the optimal hedging is the same as the hedging capacity. In the high productivity state ($s = +$, blue solid curves), when the liquidity is lower than the cutoff liquidity position, the desired hedging is constrained by the hedging capacity, so the optimal hedging is the hedging capacity. On the other hand, when the liquidity is higher than the asterisk liquidity position, the desired hedging can be achieved without violating the collateral constraint, so the optimal hedging is the desired hedging. In our calibrated model, optimal hedging is increasing in liquidity when liquidity is low, where the constraint is binding and the hedging capacity determines the optimal hedging. In the higher liquidity region, the optimal hedging is determined by the desired hedging, where it declines in liquidity over a small region and then plateaus out as a firm becomes financially unconstrained and starts to pay out dividends.

The decomposition of the optimal hedging in Panels (b) and (c) of Figure 3 connects our model to two strands of existing risk management theories. The desired hedging captures the intuition of the financial constraint-based models, where a more financially constrained firm wants to hedge more; and the hedging capacity emphasizes the collateral constraint in collateral-based models, where a firm with lower liquidity hedges less due to a tighter collateral constraint. Empirically, we only observe the optimal hedging, the minimum of desired hedging and hedging capacity. Our empirical results suggest the hedging capacity channel is more important in driving the relation between hedging and liquidity in our

[29]The hedging capacity in our model is convex in the low liquidity region, especially for the high-price state, due to the convex adjustment costs. This is different from Rampini and Viswanathan (2010) and Rampini and Viswanathan (2013), which do not have the convex investment costs.

sample, corroborating the findings in Rampini et al. (2014) and Rampini et al. (2020).

We now apply the model to explain the empirical findings. With our calibrated parameters, the desired hedging is constrained and the optimal hedging is equal to the hedging capacity most of the time, leading to an overall positive relation between optimal hedging and liquidity(Figure 3). This is consistent with our empirical finding that unrealized hedging gains are positively correlated with hedging. At the same time, optimal hedging is higher in the high productivity state ($s = +$ in Panel (a) of Figure 3), which is consistent with the positive correlation between hedging and output price we find in the data. Finally, PDD generates a negative relation between production and liquidity (Panel (b) of Figure 2). With the negative hedging to liquidity relation in Panel (a) of Figure 3, our model generates a negative relation between production and hedging. This is consistent with our empirical result that hedging and operating cash flows are negatively correlated after controlling for the output price.

Further discussion Below we discuss the importance of the two new features by showing the model predictions when either one of these two features is absent. We first show that procyclical collateral capacity is crucial in explaining the positive correlation between the hedging and productivity. In Figure 4, we present the optimal hedging policy in a model with both the collateral value, η_s, and the margin requirement, σ_s, that are independent of the productivity state s. In this case, we find that the optimal hedging is lower in the high productivity state. This result is similar to the negative hedging to productivity relation predicted by the collateral-based models such as Rampini and Viswanathan (2013) when productivity is persistent; however, this result is inconsistent with our empirical findings.

We then show that without PDD, the model cannot explain the opposite effects of operating cash flows and the output price on hedging policies. Without PDD, a firm no longer faces an intertemporal trade-off between its current and future production. Consequently, the firm is solving a static optimization problem in each period:

$$\max_{Z_t} \Pi\left(Z_t, P_t, K_t\right) \equiv \max_{Z_t} \left\{ P_t Z_t - \frac{\gamma}{2} \frac{Z_t^2}{K_t} \right\}. \tag{12}$$

This gives an optimal production to capital ratio:

$$z_t^* \equiv \frac{Z_t^*}{K_t} = \frac{P_t}{\gamma}.$$

Therefore, the optimal production is proportional to the output price, namely, the firm's productivity. As a result, operating cash flows and the output price should have the same effect on the hedging policy, contradicting our empirical findings.

4. Testing New Model Predictions

In the previous section, we extended the collateral-based models by adding procyclical collateral capacity and production-dependent depreciation (PDD). We show that these two extensions are useful in reconciling the models with the two empirical patterns we document in Section 2.2, i.e., 1) the positive correlation between output prices and hedging, and 2) the negative correlation between operating cash flow and hedging. In this section, we examine the validity of these two extensions by testing their new implications.

Reserves and Hedging Proved reserves, the primary asset of oil and gas producers[30], can be split into proved developed reserves and proved undeveloped reserves, with the value of the latter being more sensitive to the commodity price. This difference in price sensitivities offers a good setting to test our model prediction that the procyclical collateral capacity is

[30] By checking our sample firms' 10-K filings, we find that the book value of reserves accounts for more than 80% of the property, plant and equipment (PPE) on average, which in turn accounts more than 60% of the total assets.

driving the positive correlation between output prices and hedging.

Proved reserves are the amount of commodity estimated to be commercially recoverable under current economic conditions. Developed reserves are the subset that can be readily extracted , while undeveloped reserves require additional capital expenditure to extract.[31] Under the U.S. accounting system, firms need to revalue reserves through periodic impairment tests.[32] Because producing oil from undeveloped reserves incurs additional costs compared to developed reserves, the former is usually the first to be written down when the commodity price is low. In other words, the former has more procyclical value than the latter. To examine the differential procyclicality value of the developed reserves and the undeveloped reserves, we run the following regression

$$PDR\,Ratio_{it} = \alpha + \beta Price_t + \eta Controls + \gamma_i + \varepsilon_{it}\,, \tag{13}$$

where *PDR Ratio* is the proved developed to proved total reserve ratio.

Columns (1) and (2) of Table 5 show that *PDR Ratio* is negatively correlated with price shocks with at least 5% significance, with and without the firm fixed effects. This confirms the notion that proved developed reserves are less price-sensitive than proved undeveloped reserves. The relation between *PDR Ratio* and price is also negative for natural gas firms[33]; however, the regression coefficient is smaller and not statistically significant. This weaker relation is expected because the natural gas markets have remained regionally segmented

[31] See Society of Petroleum Engineers (https://www.spe.org/en/industry/reserves/) for more detailed definitions of different kinds of reserves. Besides proved reserves, an oil or gas producer may also have unproved reserves and other subcategories. However, such data are not available in a firm's financial statement. So we just focus on the developed and undeveloped reserves.

[32] For example, in the "ceiling test", a firm evaluates the value of its reserves by computing the expected net present value it can generate in the following 10 years, taking into account the expected commodity prices and the expected operating expenses. If the accounting value of the reserves exceeds this "ceiling value", the excess amount must be written down.

[33] We define natural gas (oil) firms as those deriving at least 25% of their total production, in BOE, from natural gas (oil). For the tests for natural gas (oil) firms, we define DPR based solely on natural gas (oil) reserves.

compared to oil markets. This means that the correlation between firms' gas output prices across production sites and the Henry Hub futures prices is much weaker than the correlation between firms' oil output prices and the WTI future prices. When we combine the oil and gas reserves (in BOEs), we find a negative but statistically insignificant relation between *PDR Ratio* and price.

Our model uses the procyclical collateral capacity to explain the positive hedging to price relation. If the value of the proved developed reserves is less procyclical than that of the proved undeveloped reserves, then our model will imply that the positive hedging to price relation should be weaker for firms with relatively more PDR. To test this prediction, we run the following regression in Table 6:

$$\begin{aligned} HedgeRatio_{i,t+1} = &\alpha + \beta_0 Price_t + \beta_1 PDR\,Ratio_{it} + \beta_2 Price_t \times PDR\,Ratio_{it} \\ &+ \eta Controls + \gamma_i + \varepsilon_{it}\,. \end{aligned}$$

In Columns (1) and (2) of Table 6, we find that the regression coefficient of the oil hedge ratio on the interaction term of price and *PDR Ratio* is negative and statistically significant at the 1% level. This is consistent with our model prediction that the oil hedge ratio for firms with higher *PDR ratio* has a less positive correlation with prices because the value of proved developed reserves is less sensitive to price than proved undeveloped reserves. The corresponding regression coefficients for gas hedging and the hedging are also negative, but statistically insignificant. This is expected given that the statistically insignificant *PDR Ratio* to price relation for gas (See Table 5).

Production-Dependent Depreciation (PDD) In our model, the PDD mechanism predicts that a firm produces more when liquidity is low given a price state, as in Panel (b) of

Figure 2. We test this prediction in Table 7 using the following specification:

$$\frac{Production_{it}}{Proved\,Reserves_{it}} = \alpha + \beta_1 Z\text{-}Score_{it} + \eta Controls + \gamma_i + \delta_t + \varepsilon_{it}\,.$$

Note that we do not control for the aggregate commodity prices here because we have already included the time fixed effects. Following Campello et al. (2011) and Almeida et al. (2019), we proxy liquidity using the Altman Z-score.

Overall, the empirical results in Table 7 support our model's prediction. In column (1) of Table 7, the Altman Z-score predicts the production to reserve ratio negatively, but insignificantly. Because our model predicts a convex production to liquidity relation (with the production decreasing more strongly in liquidity in the low liquidity region) we split the sample into the low and high liquidity samples based on the Z-score. We define a *High Z-Score* as a dummy that takes the value of 1 if the firm's Z-score in year t is higher than the firm's sample median Z-score, and 0 otherwise. In Columns (2) and (3), we run the same regression in the low and high liquidity samples, separately. We find that the liquidity to production correlation is negative with 5% significance in the low liquidity sample ($High\ Z\text{-}Score = 0$). In contrast, in the high liquidity sample, the correlation is actually positive. In Column (4), we use the the interaction term between Z-score and *High Z-Score* to formally test the difference in the production to liquidity relation across low and high liquidity samples. We find the loading on the interaction term is positive and highly significant, suggesting that the production to liquidity relation is more negative in the low liquidity region. Column (5) puts this test into a continuous setting. The positive significant coefficient on the squared Z-score term demonstrates that production is overall convex in liquidity, consistent with our model prediction in Panel (b) of Figure 2.

The PDD channel also predicts a negative correlation between production and investment, conditional on the price state,

$$z = \overline{z} + \frac{1}{\gamma}\left(P_s - \phi_0 - \phi i\right) . \tag{14}$$

The intuition is that production transforms reserves to liquidity, and investment transforms liquidity into future reserves. One extra unit of investment increases the next-period reserves by 1 but decreases the next-period liquidity by $-\left(\phi_0 + \phi i\right)$, whereas one extra unit of production decreases the next-period reserves by 1 but increases the next-period liquidity by $P_s - \gamma\left(z - \overline{z}\right)$. At the optimal solution, the reserve to liquidity trade-off should be identical for investment and production, and thus $-\left(\phi_0 + \phi i\right)$ is equal to $P_s - \gamma\left(z - \overline{z}\right)$. To test this prediction, we run the following regression:

$$\frac{Production_{it}}{Proved\,Reserves_{it}} = \alpha + \beta Investment_{it} + \eta Controls + \gamma_i + \delta_t + \varepsilon_{it} \, .$$

To test the negative production to investment correlation, as specified in Eq. (14), we need an empirical measure for investment in the same BOE unit as production. We hand collect such information from the Change in Reserves Statement in our sample firms' 10-K filings, as exemplified in our Appendix A.[34] Our first measure is the (net) investment in reserves, which is defined as the period-end reserves minus the period-beginning reserves adding back the depleted reserves through production. Our second measure is the active investment in reserves. We exclude revision, improved recovery, production, and other changes from the first measure because we do not consider them as active investment decisions made by the firm.

We test the production to investment correlation in Table 8. In Columns (1) and (2),

[34] The capital expenditure recorded in Compustat is not an ideal measure for two reasons. First, the reserves, investment, and production modeled in our capital dynamic (2) are in BOEs, while the Compustat measures are in dollars. Second, the expenditure recorded in Compustat includes the acquisition cost that may not turn into the next-period reserve or capital that commands a collateral value as modeled in our theoretical set-up.

we investigate the relation between production and investment over the full sample and find that both measures of investment in reserves are indeed negatively correlated to production. We include both firm and time fixed effects. Time fixed effects are important because they control for the price. In Columns (3) - (6), we again divide the sample into the low and high liquidity subsamples based on the Altman Z-score. We find that in the low liquidity subsample, the negative production to investment relation is highly significant, regardless of whether we use the the investment in reserves or the active investment in reserves measure. In the high liquidity sample, the negative production to investment relation is only significant when we use the investment in reserves measure. Overall, these results are consistent with our model prediction that production and investment are negatively correlated.

5. Conclusion

We construct a comprehensive dataset of oil and gas E&P firms' hedging positions to test risk management models' predictions on corporate hedging policies. We find that the two components of operating income – operating cash flows and unrealized hedging gains – predict hedging intensity with opposite signs (negatively and positively, respectively). Additionally, the commodity price is positively correlated with hedging intensity. Existing models have difficulty explaining these three novel empirical patterns.

To explain our empirical findings, we extend the workhorse risk management models by incorporating two realistic features – procyclical collateral capacity and the production-dependent depreciation (PDD). We show that procyclical collateral capacity helps the model generate a positive correlation between hedging intensity and the output price, while the intertemporal trade-off between current and future production in the presence of PDD is essential for generating the negative correlation between hedging intensity and operating profitability. Overall, our results shed new light on the determinants of corporate hedging policy, the key implication of risk management models.

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Figure 1: Time Series of Hedging Intensity and Commodity Price

This figure plots the average fraction of current-year oil (natural gas) production hedged and the average oil (natural gas) price for each year in our sample in the top (bottom) panel.

Figure 2: Benchmark Results

This figure presents the optimal policies of our model, except for the optimal hedging. w_1 is the net liquidity, which is defined in (9). MVC stands for the marginal value of cash (liquidity). See our Appendix D for the calibration of parameter values.

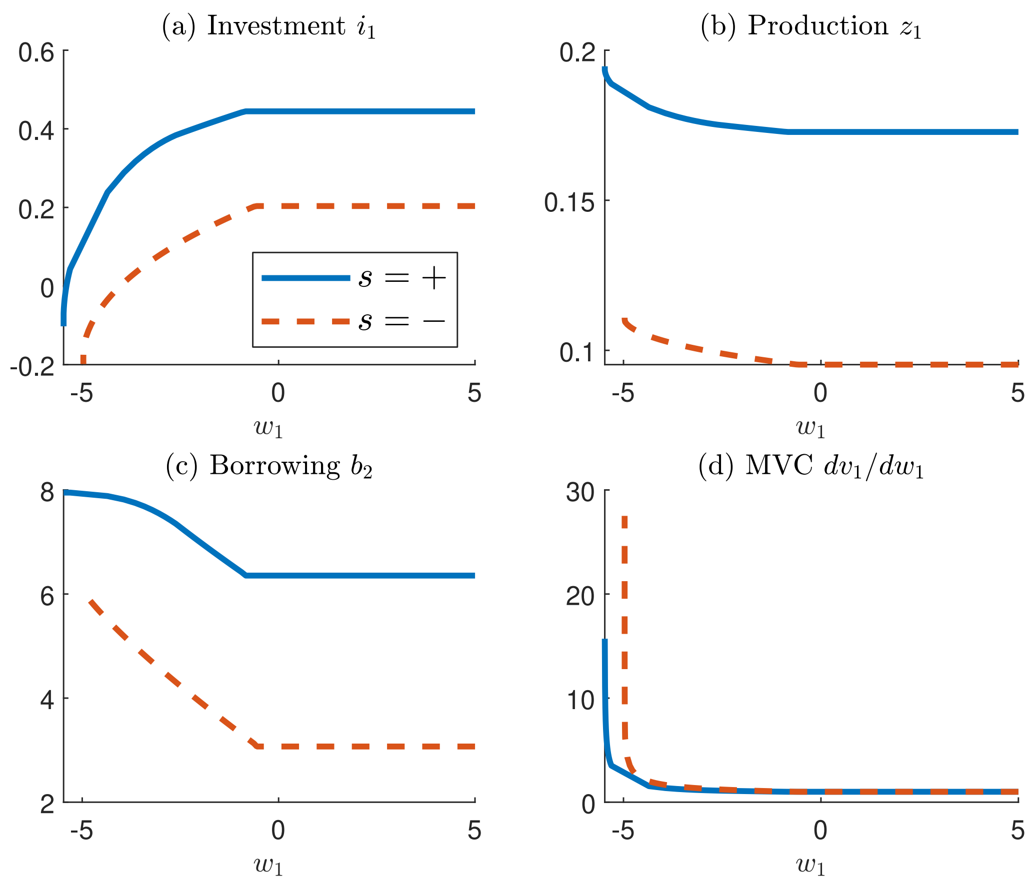

Figure 3: Optimal Hedging

This figure presents the optimal hedging policy and its two underlying components. The desired hedging is the optimal hedging as if the hedging were not subject to the collateral constraint. The hedging capacity is the maximal amount of hedging that can be attained under a binding collateral constraint. The optimal hedging is equal to Min[desired hedging, hedging capacity]. Asterisk (*) denotes the place where the desired hedging is the same as the hedging capacity in the high productivity state. The desired hedging is always above the hedging capacity in the low productivity state.

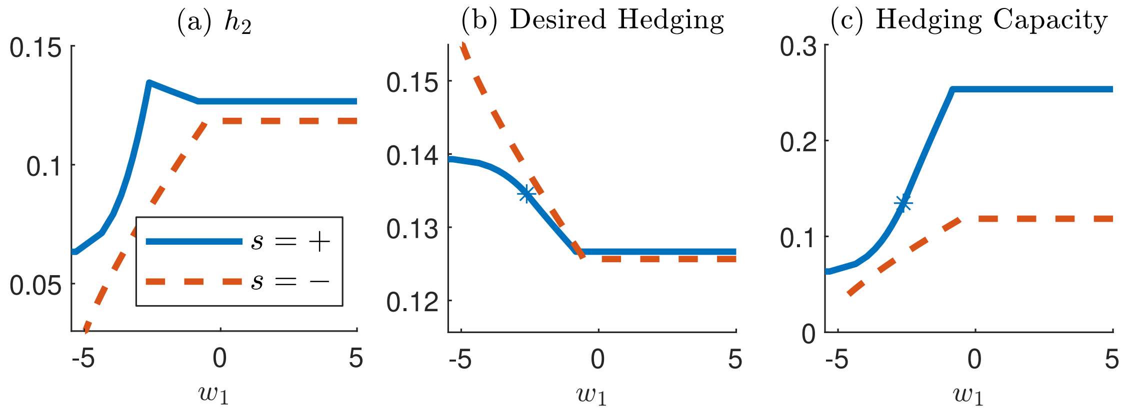

Figure 4: A Model without Procyclical Collateral Capacity

This figure plots the optimal hedging policy and its two underlying components in a model without procyclical collateral capacity. More specifically, the collateral value, η_s, and the margin requirement, σ_s, are assumed to be constant and thus independent of the productivity state s in this model. The desired hedging is the optimal hedging as if the hedging were not subject to the collateral constraint. The hedging capacity is the maximal amount of hedging that can be attained under a binding collateral constraint. The optimal hedging is equal to Min[desired hedging, hedging capacity]. Asterisk (*) denotes the place where the desired hedging is the same as the hedging capacity.

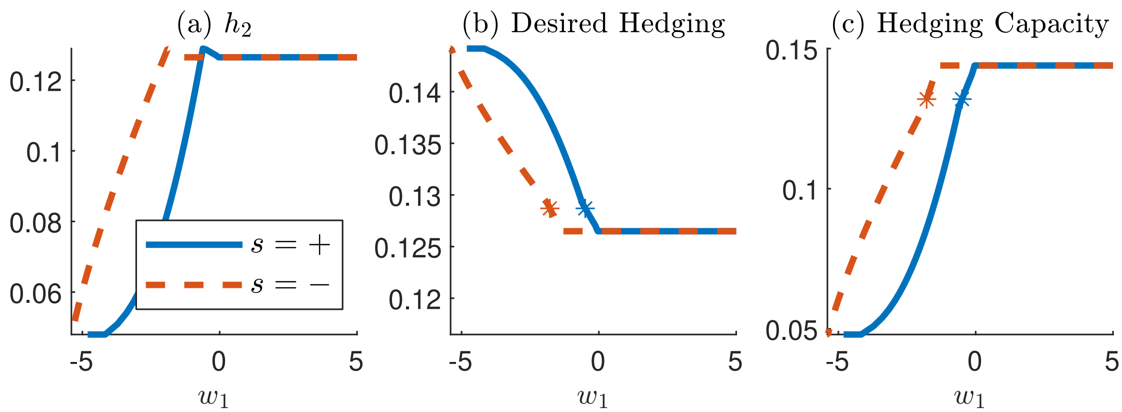

Table 1: Variable Definitions

This table defines the key variables used in the analysis and describes how they are constructed from data in financial statements. *Italicized* words in brackets are the corresponding variables in Compustat.

Variable	Definition
Hedge Ratio	The fraction of current year production that is hedged through a financial instrument
Book Value of Assets	Book value of assets (*at*)
Cash Ratio	Ratio of cash and short-term investments (*che*) to the book value of assets
Book Leverage	Ratio of the sum of long-term debt and debt in current liabilities (*dltt+dlc*) to the book value of assets
Investment intensity	Ratio of capital expenditures (*capx*) to the book value of assets
Return on Assets	Ratio of net income (*ni*) to the book value of assets
CF Operating Profitability	Ratio of cash flow from operating activities (*oancf*) to the book value of assets
Unrealized G/L on Hedging	Sum of unrealized gain/loss on cash flow hedges from accumulated other comprehensive income in shareholders' equity and unrealized gain/loss on non-cash flow hedges from income statement. Collected from the 10-K filings
Tobin's Q	Ratio of market value of assets less deferred taxes and investment tax credits ($at + prcc\_f \times csho - ceq - txditc$) to the book value of assets
Dividend Payer	An indicator taking the value 1 if the firm paid a dividend in a given year ($dvc > 0$), and 0 otherwise
Credit Rating (numerical)	We translate the letter rating from rating agencies into a numerical value. For each higher notch, the value increases by 1. For unrated firms, we use the value 0.
Developed Reserves /Production	The ratio of the developed reserves at the end of this year to next year's production

Table 2: Summary Statistics

This table presents the summary statistics of the key variables. Variable definitions are in Table 1. The sample period is 2002 to 2016.

	N	Mean	SD	P5	P25	P50	P75	P95
Hedge Ratio	738	0.490	0.308	0.014	0.273	0.484	0.681	0.936
Book Value of Assets ($ mm)	738	6191.92	10426.77	217.36	772.71	2274.97	6516.70	29736.00
Cash Ratio	738	0.037	0.058	0.000	0.003	0.014	0.047	0.147
Book Leverage	738	0.347	0.212	0.078	0.223	0.313	0.422	0.781
Return on Assets	738	-0.030	0.201	-0.394	-0.037	0.027	0.063	0.119
CF Operating Profitability	738	0.154	0.075	0.042	0.104	0.148	0.195	0.280
Unrealized G/L on Hedging	738	-0.004	0.044	-0.074	-0.017	-0.001	0.010	0.066
Tobin's Q	735	1.442	0.576	0.774	1.058	1.325	1.649	2.600
Investment intensity	738	0.258	0.123	0.087	0.167	0.234	0.344	0.482
Dividend Payer	737	0.564	0.496	0	0	1	1	1
Credit Rating (numerical)	738	7.638	5.414	0	0	9	12	15
Altman Z-Score	737	1.469	2.241	-1.933	0.644	1.482	2.245	4.233
Production/Reserves	738	0.085	0.040	0.035	0.058	0.077	0.105	0.169
Developed/Total Reserves	736	0.600	0.157	0.340	0.488	0.609	0.716	0.834

Table 3: Hedging, Financial Condition, and Investment

This table reports results from estimating the following ordinary least squares regression:

$$HedgeRatio_{it+1} = \alpha + \beta X_{it} + \gamma_i + \delta_t + \varepsilon_{it}$$

where X_{it} is a vector of theoretically motivated determinants of hedging intensity related to financial condition and profitability. Variable definitions are in Table 1. Fixed effects are included as indicated in respective columns. T denotes time fixed effects and F denotes firm fixed effects. Standard errors, reported below coefficients, are clustered at the firm and year levels. ***, **, and * denote 1%, 5%, and 10% statistical significance, respectively.

	Hedge Ratio			
	(1)	(2)	(3)	(4)
Log Assets (BV)	0.005	-0.007	0.014	0.041
	(0.019)	(0.022)	(0.030)	(0.051)
Cash Ratio	0.271	0.161	-0.111	-0.091
	(0.320)	(0.319)	(0.314)	(0.311)
Book Leverage	0.091	0.060	-0.109	-0.097
	(0.146)	(0.157)	(0.107)	(0.108)
Dividend Payer	-0.055	-0.045	-0.033	-0.023
	(0.041)	(0.040)	(0.032)	(0.033)
Credit Rating Indicator	-0.020	-0.022	0.036	0.027
	(0.051)	(0.054)	(0.050)	(0.047)
Altman Z-Score	-0.003	0.001	0.003	0.007
	(0.028)	(0.028)	(0.014)	(0.015)
Return on Assets	0.191	0.135	0.156	-0.023
	(0.171)	(0.176)	(0.130)	(0.105)
Investment intensity	0.355**	0.298	-0.000	-0.044
	(0.131)	(0.181)	(0.135)	(0.171)
Tobin's Q	0.016	0.007	0.032	0.027
	(0.045)	(0.053)	(0.020)	(0.025)
Fixed Effects	-	T	F	T,F
Observations	734	734	728	728
Adj.R^2	0.032	0.057	0.522	0.544

Table 4: Hedging and Profitability

The table reports results from estimating the following ordinary least squares regression:

$$HedgeRatio_{it+1} = \alpha + \beta X_{it} + \gamma_i + \varepsilon_{it}$$

where X_{it} consists of price and a vector of profitability variables. We also include a set of control variables in columns (3) and (4). Variable definitions are in Table 1. Firm fixed effects are included in all columns (indicated with F). Standard errors, reported below coefficients, are clustered at the firm and year levels. ***, **, and * denote 1%, 5%, and 10% statistical significance, respectively.

	Hedge Ratio			
	(1)	(2)	(3)	(4)
CF Operating Profitability	-0.653***	-0.764***	-0.371**	-0.512***
	(0.213)	(0.179)	(0.164)	(0.132)
Unrealized G/L on Hedging	0.389*	0.516**	0.680**	0.694***
	(0.199)	(0.177)	(0.300)	(0.233)
Log Prod Wtd Price		0.189***		0.178***
		(0.060)		(0.056)
Sales/Assets			-0.444***	-0.356***
			(0.133)	(0.103)
Log Assets			-0.018	-0.020
			(0.031)	(0.029)
Market to Book Value of Assets			0.054**	0.014
			(0.023)	(0.016)
Constant	0.592***	0.787***	0.731**	0.971***
	(0.042)	(0.064)	(0.251)	(0.271)
Fixed Effects	F	F	F	F
Observations	732	732	731	731
Adj. R^2	0.519	0.561	0.531	0.565

Table 5: Procyclical Value of Reserves

This table reports results from estimating the following ordinary least squares regression:

$$PDR\,Ratio_{it} = \alpha + \beta Price_t + \eta Controls + \gamma_i + \varepsilon_{it},$$

where $PDR\,Ratio_{it}$ is the ratio of proved developed reserves to total proved reserves. $Price_t$ is the log of the front month futures price for the respective fuel at the fiscal-year end. The production weighted price is production-weighted average of futures prices for the firm year. Controls include sales/assets, the log of total assets, and the market-to-book ratio. Fixed effects are included as indicated in respective columns where F denotes firm fixed effects. Standard errors, reported below coefficients, are clustered at the firm and year levels. ***, **, and * denote 1%, 5%, and 10% statistical significance, respectively.

	Ratio of Developed to Total Proved Reserves					
	Oil		Natural Gas		Both	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Oil Price	-0.062**	-0.076***				
	(0.024)	(0.018)				
Log Gas Price			0.047	-0.021		
			(0.031)	(0.023)		
Log Prod Wtd Price					-0.027	-0.031
					(0.023)	(0.022)
Constant	0.267**	0.460**	0.504***	0.927***	0.316***	0.760***
	(0.112)	(0.208)	(0.144)	(0.116)	(0.075)	(0.110)
Controls	Y	Y	Y	Y	Y	Y
Fixed Effect	-	F	-	F	-	F
Observations	428	423	600	590	735	729
Adj.R^2	0.134	0.612	0.188	0.587	0.202	0.608

Table 6: Hedging-Price Sensitivity and Procyclical Collateral

This table reports results from estimating the following ordinary least squares regression:

$$\begin{aligned} HedgeRatio_{i,t+1} = &\alpha + \beta_0 Price_t + \beta_1 PDR\,Ratio_{it} + \beta_2 Price_t \times PDR\,Ratio_{it} \\ &+ \eta Controls + \gamma_i + \varepsilon_{it}\,. \end{aligned}$$

$HedgeRatio_{i,t+1}$ is the fraction of next-year production hedged. $PDR\,Ratio$ is the ratio of proved developed reserves to total proved reserves. $Price_t$ is the log of the front month futures price for the respective fuel at the fiscal-year end. The production weighted price is production-weighted average of futures prices for the firm year. Controls include sales/assets, the log of total assets,and the market-to-book ratio. Fixed effects are as indicated where F denotes firm fixed effects. Standard errors, reported below coefficients, are clustered at the firm and year levels. ***, **, and * denote 1%, 5%, and 10% statistical significance, respectively.

	Hedge Ratio					
	Oil		Natural Gas		Both	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Oil Price	0.784***	0.933***				
	(0.226)	(0.172)				
Oil PDR Ratio	-0.703**	-0.622**				
	(0.272)	(0.226)				
Log Price × PDR ratio	-1.015***	-1.218***				
	(0.331)	(0.247)				
Log Gas Price			-0.159	0.194		
			(0.250)	(0.156)		
Gas PDR Ratio			0.664	-0.294		
			(1.019)	(0.644)		
Log Price × PDR ratio			0.335	-0.079		
			(0.335)	(0.214)		
Log Prod Wtd Price					0.101	0.272
					(0.280)	(0.234)
PDR Ratio					-0.255	-0.081
					(0.433)	(0.465)
Log Price × PDR ratio					-0.096	-0.172
					(0.398)	(0.331)
Constant	1.647***	1.287**	0.361	1.359**	0.972**	0.897*
	(0.278)	(0.463)	(0.770)	(0.492)	(0.331)	(0.498)
Controls	Y	Y	Y	Y	Y	Y
Fixed Effect	-	F	-	F	-	F
Observations	428	423	600	590	735	729
Adj.R^2	0.211	0.586	0.100	0.520	0.109	0.548

Table 7: Production and Z-Score

This table reports results from estimating the following ordinary least squares regression:

$$\frac{Production_{it}}{Proved\,Reserves_{it}} = \alpha + \beta\, Z\text{-}Score_{it} + \eta Controls + \gamma_i + \delta_t + \varepsilon_{it}\,.$$

The dependent variable is current production scaled by current proved reserves. $Z\text{-}Score_{it}$ is the Altman Z-score. *High Z-Score* is a dummy variable that takes the value of 1 if the firm's Z-score in year t is higher than the firm's median sample Z-score, and 0 otherwise. Controls include sales/assets, the log of total assets, and the market-to-book ratio. Fixed effects are included as indicated where F denotes firm fixed effects and T denotes the time fixed effects. Standard errors, reported below coefficients, are clustered at the firm and year levels. ***, **, and * denote 1%, 5%, and 10% statistical significance, respectively.

	Production/Reserves				
	All (1)	Low Z-Score (2)	High Z-Score (3)	All (4)	All (5)
Altman Z-Score	-0.043	-0.384*	0.163**	-0.328**	-0.177
	(0.090)	(0.179)	(0.069)	(0.119)	(0.114)
Z-Score × High Z-Score				0.413***	
				(0.118)	
Z-Score × Z-Score					0.018***
					(0.005)
Constant	4.281	3.750	2.150	3.555	3.017
	(2.811)	(3.582)	(3.728)	(3.021)	(2.966)
Controls	Y	Y	Y	Y	Y
Fixed Effect	F, T	F, T	F, T	F, T	F, T
Observations	731	358	356	731	731
Adj.R^2	0.742	0.723	0.836	0.746	0.745

Table 8: Production and Investment

This table reports results from estimating the following ordinary least squares regression:

$$\frac{Production_{it}}{Proved\,Reserves_{it}} = \alpha + \beta\,Investment_{it} + \eta Controls + \gamma_i + \delta_t + \varepsilon_{it}\,.$$

The dependent variable is the production scaled by the total proved reserves. Net investment is the period-end reserves minus the period-beginning reserves adding back the depleted reserves through production. Active investment in reserves exclude revision, improved recovery, production, and other changes from the net investment measure. Controls include sales/assets, the log of total assets, and the market-to-book ratio. Fixed effects are included as indicated where T denotes time fixed effects and F denotes firm fixed effects. Standard errors, reported below coefficients, are clustered at the firm and year levels. ***, **, and * denote 1%, 5%, and 10% statistical significance, respectively.

	Production/Reserves					
	All		Low Z-Score		High Z-Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Net Investment/Reserves	-3.041***		-3.141***		-3.129**	
	(0.447)		(0.421)		(1.100)	
Active Investment/Reserves		-2.730***		-3.705***		-1.322
		(0.566)		(0.480)		(1.232)
Constant	-0.807	2.184	2.810	5.149	-3.989	0.029
	(3.724)	(3.447)	(3.916)	(4.450)	(4.240)	(4.450)
Controls	Y	Y	Y	Y	Y	Y
Fixed Effect	F, T	F, T	F, T	F, T	F, T	F, T
Observations	639	643	316	316	307	310
Adj.R^2	0.788	0.762	0.804	0.777	0.838	0.822

Appendix

A. Data Appendix

A.1. Sample Construction

We identify independent oil and natural gas producers in the following steps. First, we identify domestic common stocks in the CRSP/Compustat universe that (1) have a Global Industry Classification Standard (GICS) code of 10102010 (Integrated Oil & Gas) or 10102020 (Oil & Gas Exploration & Production) or (2) have a missing GICS code but a Standard Industrial Classification (SIC) code of 1311 (Crude Petroleum and Natural Gas) during our sample period.[35] We then exclude firms with a significant refinery or downstream business by excluding those that are associated with the following GICS codes for at least one year during our sample period: 10102010 (Integrated Oil & Gas), 10102050 (Coal & Consumable Fuels), 55105010 (Independent Power Producers), or 10101020 (Natural gas distribution). If the GICS code is missing for all years, we require the firm to have a SIC code 1311 for the whole sample period.[36] Finally, we exclude microcap stocks by removing firms whose book value of total assets never exceeds $300 million during the sample period. To facilitate cross-firm comparison, we keep only firms with a fiscal year ending in December. This procedure identifies 116 unique GVKEYs, for which we then manually collect hedging data. After excluding a few firms that report derivative positions in a format substantially different from the other firms, our sample includes 112 unique GVKEYs, and 947 firm-year observations of the independent oil and gas producers.

[35] We use GICS in priority relative to SIC because cross-checking with Bloomberg reveals that GICS is more reliable than SIC identification approach. For example, SIC identification approach misses some large oil and gas producers, such as EQT, SWN, and UNT. Our approoeach identifies 207 unique GVKEYs within our sample period.

[36] After these steps, we are left with 184 unique Global Company Keys (GVKEYs).

To extract hedging data of the oil and gas producers, we write a Python program to identify and scrape tables in 10-K filings that report their hedging activities. We then manually go through all these tables and extract their contract-level details: derivative instrument types (put/call/collar options, swaps, futures/forward, and other contracts), notional volumes, maturities, strike prices (if available), and underlying commodity types (oil, gas and various liquefied gas). We aggregate the volumes of all contracts that protect the downside price risk of future production for each firm year to arrive at the hedging position. These contracts include forward, futures, swap, options, and fixed-price physical delivery contracts.[37] Finally, we compute hedging intensity as the ratio of the hedging volume for the next fiscal year over the production volume of the current fiscal year.[38] In Appendix A.2, we provide a detailed example of how we construct the hedging volume.

We drop the observations where we are unable to identify their hedging information, leaving us with 876 observations. We further exclude observations that cannot be matched to Compustat, that are non-U.S. based firms, and that do not have production data. This leaves us with 851 observations. Next, we drop firm-year observations that are delisted in the calendar year when 10-K filings are disclosed. Finally, since we focus on the variation in firms' hedging policy at the intensive margin, we drop zero-hedgers defined as firms that do not hedge in at least 50% of the years. Our final sample consists of 738 firm-year observations.

A.2. An Example of Financial Statement

APACHE CORPORATION AND SUBSIDIARIES

Form 10-K for the fiscal year ended December 31, 2009 (link)

[37] The fixed-price physical delivery contracts are similar to the purchase obligations studied in Almeida et al. (2019). Since the derivative markets for the crude oil are well developed, the usage of fixed-price physical delivery contracts is much less frequent in our sample than in Almeida et al. (2019)'s sample. Call options are excluded in our analysis as they do not pertain to downside risk management.

[38] Due to mergers and acquisitions as well as divestiture, the production volume reported in the same 10K filing as the hedging volume is a better proxy for the expected production volume than the production volume reported in the 10K filing of the following year.

Commodity Derivative Instruments

As of December 31, 2009, Apache had the following open crude oil derivative positions:

(W.A. = weighted average. Bbl is barrel of oil; BOE denotes barrel of oil equivalent; BTU is British thermal unit; CF represents cubic feet; GJ is Gigajoule. "M" is one thousand and "MM" is one million.)

	Fixed-Price Swaps		Collars		
Production Period	Mbbls	W.A. Fixed Price	Mbbls	W.A. Floor Price	W.A. Ceiling Price
2010	2,383	$68.71	10,396	$65.01	$80.84
2011	3,650	70.12	6,202	66.24	87.04
2012	3,292	70.99	2,554	66.07	89.13
2013	1,451	72.01			
2014	76	74.50			

As of December 31, 2009, Apache had the following open natural gas derivative positions:

	Fixed-Price Swaps			Collars			
Production Period	MMBtu (in 000's)	GJ (in 000's)	W.A. Fixed Price	MMBtu (in 000's)	GJ (in 000's)	W.A. Floor Price	W.A. Ceiling Price
2010	82,125		$5.81	30,550		$5.48	$7.07
2010		54,750	5.37				
2011	10,038		6.61	9,125		5.00	8.85
2011		23,725	6.75		3,650	6.50	7.10
2012	2,745		6.73	10,980		5.75	8.43
2012		29,280	6.95		7,320	6.50	7.27
2013	1,825		7.05				
2014	755		7.23				

Defining hedging position Furthermore, Apache reported in its FY 2010 10-K filing that "Australia has a local market with a limited number of buyers and sellers resulting in mostly long-term, fixed-price contracts that are periodically adjusted for changes in the local consumer price index." We consider these as fixed-price physical delivery contracts, which are also part of the hedging policies.

We define the hedging positions as follows. First, we define hedging for the next-year production as the short-term hedging and the hedging beyond one year as the long-term hedging. Second, we convert all thermal/volume units to barrel of oil equivalent (BOE) using the following conversion rule.

$$1 \text{ BOE} = 6 \text{ MMBTU} = 6 \text{ MCF} = 6.12 \text{ GJ} = 42 \text{ GAL}.$$

Third, we only count the contracts that protect firms from downside risks of the commodity prices. Therefore, in this example, the short-term oil hedging is 2,383Mbbls + 10,396Mbbls = 12,779 MBOE. The total short-term natural gas hedging is 82,125 MMBtu (in 000's) + 54,750 GJ (in 000's) + 30,550 MMBtu (in 000's) + 72.9 Bcf (Australian gas production) = 39,875 MBOE.

B. Results of Robustness Tests

Table X1: Hedging and Profitability: Excluding most distressed firms

The table reports results from estimating the following ordinary least squares regression:

$$HedgeRatio_{i,t+1} = \alpha + \beta X_{it} + \gamma_i + \varepsilon_{it} \,,$$

where X_{it} consists of price and a vector of profitability variables. We also include a set of control variables in columns (3) and (4). Variable definitions are in Table 1. Firm fixed effects are included as indicated (F). 10% of firm-year observations with the smallest Altman Z-Score are excluded. Standard errors, reported below coefficients, are clustered at the firm and year levels. ***, **, and * denote 1%, 5%, and 10% statistical significance, respectively.

	Hedge Ratio			
	(1)	(2)	(3)	(4)
CF Operating Profitability	-0.580**	-0.698***	-0.403*	-0.452**
	(0.214)	(0.190)	(0.215)	(0.186)
Unrealized G/L on Hedging	0.223	0.445**	0.429	0.599**
	(0.160)	(0.197)	(0.247)	(0.243)
Log Prod Wtd Price		0.149**		0.145**
		(0.059)		(0.057)
Sales/Assets			-0.294**	-0.315***
			(0.129)	(0.094)
Log Assets			-0.009	-0.013
			(0.029)	(0.028)
Market to Book Value of Assets			0.048*	0.015
			(0.025)	(0.020)
Constant	0.582***	0.735***	0.631**	0.865***
	(0.039)	(0.062)	(0.227)	(0.254)
Fixed Effects	F	F	F	F
Observations	653	653	652	652
Adj.R^2	0.569	0.592	0.574	0.593

Table X2: Hedging and Profitability: Instrumenting Price

The table reports results from estimating a two-stage least squares regression. In the first stage, the log of commodity price is instrumented with the Kilian (2009) Index. The results from the second stage are presented below. Variable definitions are in Table 1. Firm fixed effects are included as indicated (F). Standard errors, reported below coefficients, are clustered at the firm and year levels. ***, **, and * denote 1%, 5%, and 10% statistical significance, respectively.

	Hedge Ratio	
	(1)	(2)
Log Prod Wtd Price	0.214**	0.188**
	(0.076)	(0.078)
CF Operating Profitability	-0.779***	-0.520***
	(0.177)	(0.153)
Unrealized G/L on Hedging	0.533**	0.695***
	(0.186)	(0.231)
Sales/Assets		-0.351**
		(0.127)
Log Assets		-0.020
		(0.029)
Market to Book Value of Assets		0.012
		(0.021)
Fixed Effects	F	F
Observations	732	731
Adj.R^2	0.121	0.132
F-Statistic	8.811	9.153

C. An Example of Oil/Gas Reserve Dynamics

We provide a real world example of reserve changes, using the 2006 10-K filings of Chesapeake Energy Corporation .[39] The example illustrates how production directly reduces reserves and what investment in reserves consists of.

[39] The link is here.

Table X3: An Example of Oil/Gas Reserve Changes

This table presents the summary of changes in estimated reserves of Chesapeake for the fiscal year 2006. Its original 10-K filings are available here. Here, mbbl is the one thousand barrels of crude oil; mmcf is one thousand cubic feet of natural gas; mmcfe measures the total energy measuring in mmcf, where one mbbl of oil is considered equivalent to six mmcf of gas.

	Oil (mbbl)	Gas (mmcf)	Total (mmcfe)
December 31, 2006			
Proved reserves, beginning of period	103,323	6,900,754	7,520,690
Extensions, discoveries and other additions	8,456	777,858	828,594
Revisions of previous estimates	(3,822)	539,606	516,676
Production	(8,654)	(526,459)	(578,383)
Sale of reserves-in-place	(3)	(123)	(141)
Purchase of reserves-in-place	6,730	627,798	668,178
Proved reserves, end of period	106,030	8,319,434	8,955,614
Proved developed reserves:			
Beginning of period	76,238	4,442,270	4,899,694
End of period	76,705	5,113,211	5,573,441

D. Variables and Parameters of the Model

Table X4 presents the summarizes the definitions of variables and parameters used in the model section. In the definitions, we also include the corresponding units of the variables or the parameters, if there is one. Variable definitions are discussed in the model section already. We calibrate the model parameters using the actual data moments whenever possible. If data moments cannot directly pin down the parameter, we follow the previous literature. Risk-free rate r is 4%, the nominal interest rate during our sample period.

Aggregate parameters The borrowing rate r_B^+ is the same as the risk-free rate as the borrowing is risk-free. The saving rate r_B^- is 2% lower than the risk-free rate, following Bolton et al. (2011). The transitioning probabilities π_s are 0.2, matching the quarterly autocorrelation of oil prices of 0.88 or the annual autocorrelation of 0.6 in data. The output

Table X4: Definition of Model Variables and Parameters

This table lists the definitions of the key variables with their units and parameters used in the model section. In Panel (a), variables scaled by the level of capital K are denoted as the corresponding lower cases in the parentheses. In Panel (b), we report the parameter values used in our model section. See Appendix B for details on the calibration.

(a) Variables

Variables	Definition
s	$s \in \{+,-\}$, output price states.
K	Level of capital (BOE)
V (v)	Value function ($)
B (b)	Net debt position ($)
Z (z)	Production (BOE)
I (i)	Investment in capital (BOE)
H (h)	Hedging volume (BOE)
W (w)	Liquidity before production ($)
D (d)	Dividends ($)
μ	Lagrangian multiplier of the financial constraint, excess marginal value of cash
λ	Lagrangian multiplier of the collateral constraint, excess marginal value of collateral

(b) Parameters

Symbol	Definition	Value
r	Risk-free rate	4%
r_B	Interest rate on borrowings, $r_{B+} > r > r_{B-}$	[4%,2%]
π_s	The probability of state s transitioning to a different state.	[0.2,0.2]
P_s	Prices in state s ($/BOE)	[46.69,90.27]
$\overline{P}_s$	Expected future prices conditional on current state s ($/BOE)	[55.41,81.55]
δ	Depreciation rate	13%
$\overline{z}$	Centered production rate	3%
γ	Coefficient of convex production costs ($/BOE)	500
ϕ_0	Linear adjustment costs of investment ($/BOE)	10
ϕ	Quadratic adjustment costs of investment ($/BOE)	20
κ_s	Continuation value per capital ($/BOE)	$[12.2, 14.7]$
η_s	State-dependent unit collateral value ($/BOE)	$0.6\kappa_s$
σ_s	Maximum loss in a hedging position ($P_{\max} - \overline{P}_s$) ($/BOE)	[34.86,8.72]

prices in the two states are 46.69 ($/BOE) and 90.27 ($/BOE). We divide our full sample periods into two sub-sample periods by the oil price median, and choose the average oil prices in these two sub-sample periods to be our state-dependent prices. The expected future prices $\overline{P}_s$ are therefore

$$\overline{P}_s \equiv (1 - \pi_s)\, P_s + \pi_s P_{s-} = [55.41, 81.55] \ .$$

Parameters related to production and investment The depreciation rate δ is 13%, the average depreciation over PPENT from Compustat within our sample. The centered production rate $\overline{z}$ is 3% and the convex adjustment cost for production γ is 500, which we choose to match the average firm value in our model to the conditional mean of the market-to-book ratio of equities in data. As most firms' costs of reserves are ranging from $5-$15 per BOE, we just choose the linear adjustment costs of capital ϕ_0 to be 10 ($/BOE). The coefficient of quadratic adjustment costs of investment is 20, which is twice of that of the linear one. This is similar to the choice of many quantitative theory models, such as Riddick and Whited (2009) and Bolton et al. (2011).

Parameters related to financing and continuation Continuation value at the end of date 2 $\overline{\kappa}_s$ is 12.2 and 14.7 ($/BOE) for the low- and high-price states, respectively, which correspond to the average market value of equity to proved reserves ratios in data. Collateral value coefficient η is chosen to be 0.6 of the continuation value, as we assume that only 60% of the future value of the firm can be credibly committed as collateral. Maximum loss in a hedging position σ_s is $P_{\max} - \overline{P}_s = [34.86, 8.72]$.

E. Details of Model Solutions

Scaling all variables by capital K_t and using the definition of net liquidity w as in (9), we obtain an equivalent problem

$$v(w,s) = \max_{z,i,b',h'} \left\{ d + \frac{1+i-z-\delta}{1+r} Ev(b',s') \right\} \tag{15}$$

$$\text{s.t. } d = w + \left(P_s z - \frac{\gamma}{2} z^2\right) - \left(\phi_1 i + \frac{\phi_2}{2} i^2\right) + (1+i-z-\delta)\, b' \geq 0, \tag{16}$$

$$\eta_s \geq (1+r_B)\, b' + \sigma_s h' \, . \tag{17}$$

For this recursive problem, we use $\cdot'$ to denote next period variables and the others are current period variables.

The Lagrange multipliers for the financial and collateral constraints are denoted as μ and $(1+i-z-\delta)\,\lambda$, respectively. Therefore, μ and λ denote the marginal value of liquidity and collateral, respectively. We obtain the following Lagrangian equation

$$\begin{aligned} \mathcal{L}(w,s) = \max_{z,i,b',h'} & \frac{1+i-z-\delta}{1+r} Ev(w',s') + (1+i-z-\delta)\,\lambda\left[\eta_s - (1+r_B)\,b' - \sigma_s h'\right] \\ & + (1+\mu_s)\left[w + P_s z - \frac{\gamma}{2} z^2 - \left(\phi_1 i + \frac{\phi_2}{2} i^2\right) + (1+i-z-\delta)\, b'\right] . \end{aligned}$$

First of all, the first-order conditions (hereafter FOC) are

$$[i] : (\phi_1 + \phi_2 i - b')(1+\mu) = \frac{1}{1+r} Ev(w',s') \tag{18}$$

$$[z] : -(P_s - \gamma z + b')(1+\mu) = \frac{1}{1+r} Ev(w',s') \tag{19}$$

$$[b'] : 0 = -\frac{1+r_B}{1+r} Ev_w(w',s') + (1+\mu) - (1+r_B)\,\lambda \tag{20}$$

$$[h'] : 0 = \frac{1}{1+r} E\left[\left(\overline{P}_s - P_{s'}\right) v_w(w',s')\right] - \lambda\sigma_s \tag{21}$$

The first two equations imply a relation between production z and investment i:

$$\begin{aligned} P_s - \gamma z &= \phi_1 + \phi_2 i \\ z &= \frac{1}{\gamma}\left[P_s - \phi_1 - \phi_2 i\right] . \end{aligned} \tag{22}$$

In the following derivations, to simplify notations, we denote

$$\begin{aligned} \hat{\alpha}_s &\equiv \frac{P_s^2}{2\gamma} + \frac{\phi_1^2}{2\phi_2} \\ \hat{\beta}_s &\equiv 1 - \delta - \frac{\phi_1}{\phi_2} - \frac{P_s}{\gamma} \\ \hat{\phi} &\equiv 1/\left(\frac{1}{\gamma} + \frac{1}{\phi}\right) \end{aligned}$$

then the financial constraint (16) can be written as

$$d = w + \hat{\alpha}_s + \hat{\beta}_s b' + \frac{1}{2\hat{\phi}}\left(b'\right)^2 - \frac{1}{2\hat{\phi}}\left(\phi_2 i + \phi_1 - b'\right)^2 . \tag{23}$$

We solve our two-state ($s \in \{+,-\}$) and two-period ($t = 1,2,3$) model backward by dates. At date 3, the firm is liquidated with unit liquidation value of reserve being κ_s, i.e., $E_2\left(v_3 | s_2 = s\right) = \kappa_s$. So the investment FOC (18) for period 2 becomes

$$\left(\phi_1 + \phi_2 i_2 - b_3\right)\left(1 + \mu_2\right) = \kappa_s$$

since $b_3 = 0$,

$$i_2\left(s_2\right) = \frac{1}{\phi_2}\left(\frac{\kappa_s}{1 + \mu_2} - \phi_1\right) . \tag{24}$$

We can then derive the optimal policies at date 2. When the firm at date 2 is financially constrained, i.e., $\mu_2 > 0$, we have (fcon denotes financially constrained)

$$i_{2,fcon} = -\frac{\phi_1}{\phi_2} + \frac{1}{\phi_1}\sqrt{2\hat{\phi}\left(w_2 + \hat{\alpha}_s\right)},$$
$$v_{2,fcon}\left(s_2\right) = \kappa_s\left(1 - \delta + i_{2,fcon} - z^*_{2,fcon}\right) = \kappa_s\left(\hat{\beta}_s + \sqrt{\frac{2}{\hat{\phi}}\left(w_2 + \hat{\alpha}_s\right)}\right).$$

Similarly when the firm at date 2 is not financially constrained, i.e., $\mu_2 = 0$, we have (func denotes financially unconstrained)

$$w_2 \geq \overline{w}_2 \equiv \frac{1}{2\hat{\phi}}\kappa_s^2 - \hat{\alpha}_s$$
$$i_{2,func} = -\frac{\phi_0}{\phi} + \frac{1}{\phi}\kappa_s$$
$$v_{2,func}\left(s_2\right) = \left(w_2 - \overline{w}_2\right) + \kappa_s\left(\hat{\beta}_s + \frac{\kappa_s}{\hat{\phi}}\right).$$

Combining these with (24), we can solve for μ_2 and thus i_2 and v_2 given (w_2, s_2).

We then solve for the optimal hedging policy h_2. When the collateral constraint is not binding (denote this case to be cunc), i.e., $\lambda_2 = 0$, the firm can transfer intra-temporally the financial resources between two states at date 2, i.e.,

$$0 = \pi_{s1,-}\left(\overline{P}_{s1} - P_-\right)\frac{\partial}{\partial w}v_2\left(w_{2-}, -\right) + \pi_{s1,+}\left(\overline{P}_{s1} - P_+\right)\frac{\partial}{\partial w}v_2\left(w_{2+}, +\right).$$

which yields

$$\frac{\partial}{\partial w}v_2\left(w_{2-}, -\right) = \frac{\partial}{\partial w}v_2\left(w_{2+}, +\right).$$

Denote the ratio of continuation value $\Delta_P \equiv \frac{\overline{\kappa}_-}{\overline{\kappa}_+}$. We have

$$h_{2,cunc}\left(b_2, s_1\right) = \frac{\left(\hat{\alpha}_+\Delta_P^2 - \hat{\alpha}_-\right) + \left(1 - \Delta_P^2\right)\left(1 + r_B\right)b_2}{\left(\overline{P}\left(s_1\right) - P_-\right) - \left(\overline{P}\left(s_1\right) - P_+\right)\Delta_P^2}.$$

Here, we find that the sensitivity of $h_{2,cunc}$ w.r.t. productivity actually depends on the ratio of continuation value, which further depends on persistence of P. We notice that the optimal hedging is strictly increasing with b_2 as $\Delta_P < 1$. We can also say $h_{2,cunc}$ is the *desired hedging* if the collateral constraint is not binding.

When the collateral constraint is binding, i.e., $\lambda_2 > 0$,

$$h_{2,ccon} = \frac{\eta_{s1} - \left(1 + r^B\right) b_2}{P_+ - \overline{P}\left(s_1\right)},$$

where ccon denotes the case that collateral constraint is binding. This gives the *hedging capacity*, the maximum hedging position a firm can achieved, the same as in (11).

Given the above solutions on value function and optimal hedging policies as functions of (b_2, s_1), we can further solve the problem at date 1. Define $u(b', s)$ in the following way:

$$u(b', s) \equiv \max_{h'_s} \left\{ \frac{1}{1+r} Ev(w', s') + \lambda \left[\eta_s - (1 + r_B) b' - \sigma_s h'\right] \right\}.$$

then date-1 investment becomes

$$i_1(b_2, s_1) = \begin{cases} \frac{b_2 - \phi_1}{\phi_2} + \frac{1}{\phi_2}\sqrt{2\hat{\phi}\left[\hat{\alpha}_{s1} + \beta_{s1} b_2 + w_1\right] + b_2^2} & \text{if } s1 \text{ is financially constrained} \\ \frac{1}{\phi_2}\left(u(b_2, s_1) + b_2 - \phi_1\right) & \text{if } s1 \text{ is financially unconstrained}. \end{cases}$$

Finally, $z_1(b_2, s_1)$ can be solved based on (22). So all policy variables (i_1, z_1, and h_2) and the future expected value $u(b_2, s_1)$ have been expressed as functions of (b_2, s_1). We only need solve the optimal borrowing policy b_2 as a function of date-1 state variables (w_1, s_1). Plugging everything back in the FOC for borrowing (20) at date 1, we eventually arrive at several quartic equations of $b_2(w_1, s_1)$ for all possible scenarios of (w_1, s_1). Solving them, we arrive at our model solution, which is presented in Section 3.