Information Transparency and Risk Sharing in Commodity Futures Markets

by

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Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Business Administration
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ABSTRACT

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Abstract

A central function of commodity futures markets is to help firms in the real sector insure against commodity price fluctuations. I examine how greater availability of information about commodity fundamentals (henceforth, information transparency) affects the capacity of these markets to accommodate firms' hedging needs. Theory suggests that while greater availability of information can reduce adverse selection and increase traders' willingness to absorb risk, it can also accelerate the realization of risk and hinder the transfer of risk via the markets. Using both cross-sectional variation in information transparency across 26 commodity markets over 20 years and information shocks induced by the launch of the Agricultural Market Information System (AMIS) and the SEC's revision of firms' 10-K oil and gas reserve disclosures, I document that information transparency (i) makes it costlier to use commodity futures to hedge commodity price risk and (ii) reduces traders' propensity to trade futures. Evidence suggests that these findings are consistent with theories positing that information disclosure impairs risk-sharing opportunities. This study contributes new evidence on how information influences the efficient allocation of commodity price risk across the real and financial sectors.

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1. Introduction

Commodity futures play a central role in assisting producers and users to hedge commodity price risk. Commodity price fluctuations that firms face increase the likelihood of low cash flow realizations that may result in financial distress and underinvestment. Many firms mitigate such price risk by trading commodity futures to obtain a form of price insurance from the futures markets. Not surprisingly, over the past two decades these markets have been growing at around 20% annually, reaching $60 trillion in notional value and becoming one of the most significant and successful risk-sharing markets in the economy (World Federation of Exchanges, 2022). At the same time, policymakers have shown considerable interest in publishing information and data about commodity fundamentals, such as commodity supply and demand conditions.[1] This paper studies the role of such fundamental information disclosure in commodity futures markets and assesses its impact on the markets' capacity to meet commercial hedgers' hedging needs.

Commodity futures markets are dominated by two types of participants: commercial hedgers and noncommercial financial traders (e.g., hedge funds, other money managers, and index traders).[2] While hedgers trade futures to reduce their exposure to commodity price risk, financial traders speculate or seek diversification benefits through futures. At an aggregate level, hedgers'

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[1] In the United States, the public dissemination of market information by the government for agricultural commodities has a long history, going back more than a century (Allen, 1994; Garcia et al., 1997). For energy markets, the U.S. Congress created the Energy Information Administration (EIA) in 1977 to provide data, including forecasts for and analyses of energy supply and consumption. Over the past two decades, this interest in transparency has been further strengthened. The International Organization of Securities Commissions (IOSCO) and the Commodity Futures Trading Commission (CFTC) both called for improvements in the availability and quality of commodities-related information in the 2010s. However, public commodities information initiatives require significant public resources. For instance, for agricultural commodities alone, the 2022 federal budget for the National Agricultural Statistics Service ran to $212 million (USDA, 2022).

[2] For brevity, in later sections, I refer to commercial hedgers as "hedgers" or "commercials"; I refer to noncommercial financial traders as "financial traders" or "noncommercials."

demand for price insurance in commodity futures markets is met primarily by financial traders.[3] Through trading, the markets effectively transfer the risk from hedgers to financial traders who are more able and willing to bear it, thus improving risk reallocation in the economy.

Economic theories suggest two channels through which information disclosure can affect the efficiency of this risk sharing in commodity futures markets. On the one hand, information about commodity fundamentals could reduce insurance opportunities provided by the markets to hedgers (e.g., Hirshleifer, 1971; Eckwert and Zilcha, 2001, 2003; Vives, 2010). In the absence of information disclosure, hedgers can trade futures to lock in *ex ante* fixed selling or purchasing prices for commodities. If an information signal is released and reveals a commodity's value, futures price for that commodity will adjust to reflect this value, and those hedgers for which the price movement is not favorable will miss out on the chance to secure better prices using futures, which would have been possible without the information. Even when the information disclosed is not perfectly precise but more becomes readily available, the portion of the price risk revealed by the information becomes uninsurable using futures. Only the unrevealed portion of the risk can be traded, thus limiting opportunities to reallocate risk through trade, which forces hedgers to bear greater risk that could otherwise be transferred to others.

Alternatively, disclosure may improve risk sharing for hedgers if there exist information asymmetries among market participants. Traders may be reluctant to trade if they fear that other parties have an information advantage (Akerlof, 1970; De Roon et al., 2000). Such adverse selection can be quite severe in commodity futures markets given uncertainty in fundamentals stemming from the globalization of commodities and the absence of insider trading restrictions for

[3] Research on price insurance provision by financial traders to hedgers dates back to the theory of normal backwardation (Keynes, 1930, 1923) and Friedman (1960).

futures (Verstein, 2016). Without enough participants, the markets' risk-bearing capacity diminishes, resulting in less efficient risk sharing (Hirshleifer, 1988; 1990). Greater information provision can reduce adverse selection and encourage participation by less informed traders, expanding the supply of price insurance (Vives, 2010).

As the above two opposing forces are not mutually exclusive and their relative importance is unknown, the net impact of information transparency on the markets' capacity to accommodate hedgers' risk-sharing needs is unclear. This paper conducts the first empirical study of the impact of information transparency on the markets' risk-sharing function and the underlying economic channels.

I begin by examining whether the markets' capacity to meet hedgers' demand for price insurance varies systematically with the degree of transparency in a large sample of 26 major commodities traded on four North American exchanges (NYMEX, NYBOT, CBOT, and CME) from 1994 through 2020. To estimate variation in transparency in a given commodity market, I develop a summary measure, *Info_Transp*, that captures the degree to which futures prices contain information about future spot prices. Centralized futures market trading aggregates dispersed information by market participants; thus, commodity futures prices summarize available information about fundamentals (Danthine, 1978). All else equal, markets with higher values of *Info_Transp* are more transparent because there is more information about commodity fundamentals available. To assess the markets' ability to fulfill hedgers' demand for price insurance, I rely on a recent innovation in the finance literature that isolates the price impact of hedging-motivated trades (also called hedging pressure) to measure how costly or difficult it is for hedgers to obtain price insurance (Kang et al., 2020). I expect the price impact to increase as the markets' capacity to supply price insurance becomes more constrained.

I document a statistically significant positive association between my summary measure of transparency, *Info_Transp*, and the price impact of hedging pressure. The economic magnitude is large—a within-unit one-standard-deviation increase in transparency amplifies the price impact of hedging pressure by 73%, which is comparable to the influence of other first-order determinants of price insurance provision, such as financial traders' risk tolerance (e.g., Acharya et al., 2013; Cheng et al., 2015).[4] This finding indicates that, when markets become more transparent, hedgers experience a substantial tightening of price insurance provision and incur higher costs to transfer risk.

To triangulate the results regarding price impact, I examine whether the increased cost of price insurance manifests in hedgers' trading activities. All else equal, markets will accommodate fewer hedging-motivated trades when the supply of price insurance shrinks (Medrano and Vives, 2004; Vives, 2010). Consistent with this conjecture, I document a reliably negative relationship between *Info_Transp* and hedgers' propensity to trade. I find that financial traders—the key traders who fulfill hedgers' risk-sharing needs—also exhibit a diminished propensity to trade. These baseline results are robust to the inclusion of a comprehensive set of controls and rigid fixed effects and conservative treatment of standard errors. Taken together, these findings suggest that, on average, transparency compromises the markets' capacity to accommodate hedgers' needs.

One concern is that the reduction in trading intensity might reflect hedgers' diminished hedging incentives if information provision reduces the price risk that hedgers seek to hedge. This is possible if more information about future commodity fundamentals facilitates hedgers' production and consumption decisions, which in turn smooth out the demand and supply shocks of

[4] Acharya et al. (2013) show that a one-standard-deviation change in speculator risk tolerance is associated with a 50-75% change in the price impact of producers' fundamental hedging demand.

commodities. To the extent that lower price volatility would reduce price impacts holding all else equal (Ekeland et al., 2019; Goldstein and Yang, 2022), the positive relationship between transparency and the price impact of hedging pressure I document suggests that the adverse risk-sharing effect outweighs any changes in price volatility.

Another related concern is that when hedgers have better information to make production and consumption decisions, they may reduce their hedging demand. It is ex-ante unclear that this would be the case. For example, if producers know that the future spot price of a commodity will increase, they will increase their production and hence their hedging demand. Furthermore, if hedging demand does decrease and this decrease drives the decrease in trading, then the cost of hedging should be lower. However, this is not the case. I find that when information transparency is high, the cost of hedging increases. The significant increase in the cost of hedging rules out the possibility that a decline in hedging demand drives the reduction in trading.

Finally, it is plausible that the broad cross-sectional results are driven by omitted correlated variables. To address this concern, I exploit the G20's 2011 introduction of the Agricultural Market Information System (AMIS) as a large and mandatory shock to public information availability in several agricultural markets. The AMIS is a publicly accessible information system that processes and disseminates a wealth of information about current and forecasted supply, demand, and inventory conditions of agricultural commodities. I examine how its launch affects the markets' capacity to meet hedgers' risk-sharing needs. The analyses using this setting also shed light directly on the consequences of one of the most significant transparency initiatives in commodity markets.

I first validate that this setting represents a positive information shock by showing that it results in a significant increase in the available information, as captured by futures prices. Futures price informativeness increases by approximately 67% around the AMIS launch. I then use the AMIS setting in difference-in-differences analyses that compare changes in risk-sharing outcomes for affected commodities relative to those for other commodities around the shock. I document that this plausibly exogenous improvement in transparency reduces traders' propensity to trade and raises hedging costs, consistent with the baseline results. The treatment and control markets follow similar pre-trends and the results cannot be explained by the financialization of commodity markets. The results are also robust to using the revision of SEC 10-K oil and gas (OG) reserve reporting disclosures in 2009 as an alternative setting. Taken together, these results support a causal interpretation according to which the documented effects are driven by changes in the availability of public information.

Next, I perform several analyses to shed light on the underlying mechanisms driving the observed reduction in price insurance provision. I investigate whether the reduction reflects a deterioration in the risk-sharing potential of the markets. First, if the markets become less efficient in accommodating hedgers' risk-sharing needs, one would expect that, for a given level of fundamental hedging demand, hedgers' equilibrium hedging positions would shrink. Accordingly, I examine whether changes in hedgers' hedging positions become less sensitive to increases in their fundamental hedging demand around the AMIS launch. Following risk management research that links corporate hedging demand to managerial aversion to distress and default (e.g., Acharya et al., 2013; Stulz, 1984), I identify hedgers' inclination to hedge at the micro-level using public commodity firms' default risk and aggregate it at the commodity level based on the firms' exposure to a given commodity. I find that the sensitivity of hedgers' hedging positions to the aggregate default risk at the commodity level declines after the AMIS launch.

Second, I turn to financial traders' diversification-motivated trading to infer the potential of the markets to provide diversification benefits. If previously documented effects stem from the revelation of information that eliminates certain states of the world where agents can insure each other, then the reduction in risk-sharing opportunities should simultaneously affect financial traders' diversification-motivated trading, which is another form of risk sharing. Financial traders who seek diversification benefits through commodity futures include futures in their portfolios to hedge exposure to other financial assets, such as stocks. Their diversification motives are expected to be strong when the stock market is in distress because of the negative correlation between commodities and stocks arising from opposite inflation sensitivities. Empirically, Chen et al. (2019) show that, during stock market downturns, hedge fund investment in commodity futures provides significant diversification benefits, driving investor inflows. I find that, after the AMIS was implemented, the net inflows of financial traders to agricultural markets during stock market downturns drop, indicating that the traders find these markets less attractive in providing diversification benefits. These two sets of evidence collectively suggest that when markets become more transparent they become less desirable places for hedgers and financial traders to share risks.

To further substantiate the risk-sharing channel, I test whether the results vary in the cross-section as predicted by theory by exploiting the variation in the dispersion of market positions. Eckwert and Zilcha (2003) posit that information revelation tends to be more harmful in markets that offer better hedging opportunities. Intuitively, if more risk is allocated efficiently *ex ante* via the markets, releasing information that resolves this risk would result in a greater loss of risk-sharing opportunities. I hypothesize that markets that allocate risk more efficiently are typically occupied by more widely dispersed groups of traders because, in these markets, trading needs at the aggregate level tend to be less correlated and risk can be more easily transferred. Consistent with Eckwert and Zilcha's (2003) prediction, I find that the AMIS launch results in a greater decline in the supply of price insurance in markets with more dispersed market positions: the effect is about five times larger where market positions are more dispersed than where they are more concentrated.

Finally, I explore whether transparency, as suggested earlier, also affects price insurance obtained by hedgers by alleviating information asymmetry. I exploit variation in trader sophistication, an important determinant of information asymmetry, in the preperiod. If transparency affects price insurance supply by altering information asymmetry, then the effect should vary across markets with different distributions of trader sophistication. I measure hedgers' and financial traders' sophistication respectively by their average position size, given that traders holding larger positions likely have greater resources and skills to generate private information about commodity fundamentals. I find that the price-insurance-reduction effect becomes insignificant in markets where hedgers are more sophisticated. This finding suggests that public information via the AMIS likely reduces hedgers' information advantage, making financial traders more willing to accommodate hedgers' demand for price insurance and offsetting the previously documented reduction in the supply of price insurance. However, this beneficial adverse-selection effect of public information is immaterial and, in an average market, is outweighed by the detrimental risk-sharing effect.

My study makes several contributions to the academic literature and practice. To the best of my knowledge, this is the first study to document the impact of information disclosure on risk sharing in commodity futures markets. Policymakers have promoted transparency in these markets for decades, yet evidence of its benefits and costs remains limited. A large body of research on equity markets shows that public information benefits traders by improving liquidity (e.g., Balakrishnan et al., 2014; Leuz and Verrecchia, 2000; Shroff et al., 2013), but these findings may not necessarily translate to commodity futures markets, which are designed to share risk among traders. My study provides direct evidence that greater transparency could reduce commodity futures markets' capacity to meet traders' needs and hinder the flow of risk in the economy.

At the same time, the extant literature on the role of information disclosure in commodity futures markets focuses on the information content of public announcements about commodity fundamentals and the corresponding short-window futures market reactions.[5] These studies generally document positive informational value in announcements. My findings confirm that disclosures about commodity fundamentals (e.g., from the AMIS) have informational value, and I extend this literature by focusing on how disclosures affect the markets' core risk-sharing function. This study speaks to the trade-off between price discovery and risk sharing in financial markets (Dye, 2001; Eckwert and Zilcha, 2003; Goldstein and Yang, 2022; Rahi, 1995), yielding new evidence to help determine the optimal level of information disclosure (Goldstein and Yang, 2017).

This study also adds to the literature on the determinants of risk-sharing efficiency in commodity futures markets. Modern hedging theory posits that risk sharing may be inefficient in these markets because market imperfections, such as financial constraints and informational barriers, can preclude traders from participating (e.g., Hirshleifer 1988, 1990). The empirical literature has focused predominantly on frictions arising from financial traders' capital constraints and risk aversion (Acharya et al., 2013; Brunetti and Reiffen, 2014; Cheng et al., 2015; Etula, 2013). My study demonstrates how disclosure interacts with informational frictions and alters risk-sharing efficiency. I also design novel approaches with which to assess the markets' risk-sharing potential.

Lastly, this study contributes to the broader literature on the economic consequences of information disclosures. The accounting literature documents various benefits and costs of public information concerning the efficiency of resource allocation.[6] I show how information disclosures shape the efficiency of *risk reallocation* in the economy and could cause economic agents to bear

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[5] See, for example, Huang et al. (2021), Irwin et al. (2001), Isengildina-Massa et al. (2021), Isengildina-Massa et al. (2016), Isengildina et al. (2006), Mckenzie (2008), and Ying et al. (2019).

[6] See Roychowdhury, Shroff, and Verdi (2019), Kim and Valentine (2021), Jayaraman and Wu (2019), and Balakrishnan et al. (2014), among others.

too much risk. Furthermore, although the theoretical literature on the adverse risk-sharing effect of public information is well-developed, there is limited empirical evidence supporting its existence in financial markets.[7] This paper complements Ball (2013), who validates the adverse risk-sharing effect in a stock market setting, by providing distinct evidence in the context of commodity futures markets, where risk sharing motivated the creation of these markets. In doing so, I answer the call from Verrecchia (1982) and identify an important, well-defined institutional setting to study the social value of information.[8] Finally, I document the risk-sharing consequences for different traders and provide some of the first evidence that information disclosure affects markets' capacity to accommodate financial traders' diversification-motivated trading across segmented markets. This finding has broad implications given the growing prominence and relevance of cross-market trading in today's markets (Goldstein et al., 2014).

[7] See Verrecchia (2001, 1982) for a review of the theoretical literature on this topic.

[8] In discussing the theoretical literature on the Hirshleifer Effect, Verrecchia (1982) commented, "While an awareness of the existence of a redistributive effect may be vital to our understanding of the problem, it was given a disproportionate amount of attention. Understanding circumstances in which information does, or does not, have 'social value' seems to be of limited use if, *at a practical level, those circumstances cannot be identified*" (emphasis added).

2. Institutional Background, Theoretical Framework, and Related Literature

2.1 Value of Commodity Hedging

Commodity futures are designed to facilitate efficient risk sharing for producers, processors, and end users. Many firms are exposed constantly to commodity price risk; e.g., food processors face ever-changing crop prices and airlines are subject to higher fuel costs caused by rising oil prices. In a survey by Giambona et al. (2018), 31% of risk managers reported facing material commodity price risk and 54% of CFOs reported perceiving a rise in the risk between 2006 and 2010. Fluctuations in commodity prices paired with capital market imperfections can impose considerable financial contracting costs. Escalating purchase prices of raw materials or unfavorable output prices may deplete or reduce firms' internal cash flows, requiring managers to seek costly external financing to fund projects or to forego profitable investment opportunities (Froot et al., 1993). A shortfall in internal funding can also push a firm toward financial distress and even bankruptcy (Smith and Stulz, 1985).

The use of commodity derivatives to hedge price risk can reduce this risk *ex ante* and increase corporate value.[9] By trading commodity derivatives, firms can offset their exposure to commodity price risk, reducing the probability that realized cash flows result in financial distress. Reducing cash flow volatility also provides firms with sufficient internal funds to pursue investment opportunities.[10] This hedging benefit is significant: for example, Carter et al. (2006) find that jet fuel hedging is associated with a 5% to 10% increase in airline values. Perhaps

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[9] These instruments include forward contracts, futures contracts, fixed pricing contracts, swaps, options, etc.

[10] For empirical evidence of the beneficial effect of risk management on corporate value, see Campello et al. (2011), Gilje and Taillard (2017), and Pérez-González and Yun (2013), among others.

unsurprisingly, approximately 50% of Fortune Global 500 companies use financial derivatives to manage commodity price risks, with utilities and basic materials companies' usage as high as 80% (ISDA, 2009).

2.2 Risk Sharing in Commodity Futures Markets

Among commodity derivatives, futures are widely used as a primary hedging tool; 34% of respondents to the Giambona et al. (2018) survey who indicated they manage commodity price risk via derivatives reported the use of commodity futures to hedge. Commodity futures markets provide a centralized platform for transferring risks between market participants. At the aggregate level, hedgers' demand for price insurance is accommodated by financial traders who do not have exposure to physical commodities but trade for diversification and speculation. These financial traders include hedge funds, other managed money vehicles, and commodity index traders (CITs).

Hedge funds and money managers include commodity trading advisors (CTAs), commodity pool operators, and any persons or institutions that manage money, such as pension and endowment funds. These entities invest clients' funds in commodity futures, potentially alongside other financial instruments, and trade using various investment strategies and significant leverage. In aggregate, their trading exhibits both speculation and diversification motives. To speculate, actively managed funds employ momentum strategies by going long in past winners and short in past losers and/or perform fundamental analysis.[11, 12] To diversify, some passive (unmanaged) funds

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[11] Empirical evidence shows that momentum is a dominant investment style among hedge funds (Fung and Hsieh, 2001, 1997; Kang et al., 2020; Moskowitz et al., 2012). A survey in 2000 cited by Bhardwaj et al. (2014) and Waksman (2000) indicates that around 70% of CTAs identify themselves as trend followers and pursue momentum strategies.

[12] Some hedge funds forecast price movements by gathering and analyzing information about commodity supply and demand, weather patterns, macroeconomic policies, etc., and trade on such information. One example is Rosetta Capital Management (RCM), a hedge fund that invests in grains and meats commodity markets. On its website (https://www.rosettacm.com/), RCM notes that it "has established an extensive network of contacts in all phases of the commodity and derivative markets, ranging from producers to pit brokers. This network yields an abundance of market information and includes access to internal and external meat, grain and weather research. The ability to utilize such a

track the performance of commodity indices that include baskets of commodity futures. Furthermore, CTAs are shown to provide their investors with significant diversification benefits (against stock market downturns) that attract investor inflows (Chen et al., 2019), suggesting that financial investors invest in commodity funds in part to seek diversification benefits.

CITs represent individual and institutional investors who seek exposure to indices based on baskets of commodity futures, e.g., the S&P GSCI and the Dow Jones-UBS Commodity Index (DJ-UBSCI). They gain this exposure by investing in commodity index swaps, exchange-traded funds, and exchange-traded notes. Issuers of these products, such as financial swaps dealers, in turn, hedge their exposure by maintaining long positions in individual commodity futures and rolling their contracts forward based on predetermined schedules.

Like commercial hedgers, financial traders with diversification motives use commodity futures as risk-sharing instruments. They maximize expected returns by employing futures to hedge their investments in other assets whose payoffs are correlated with commodity futures. Hence, commodity futures markets also accommodate the risk-sharing needs of financial traders.

2.2.1 Price Insurance Provision by Financial Traders and Informational Frictions

According to the traditional theory of normal backwardation (Hicks, 1939; Keynes, 1930), financial traders play a key role in accommodating hedgers' demand for price insurance when hedgers trade to share commodity price risk. This theory posits that hedgers are net long in physical markets in aggregate and hence take a net short position in futures. To attract financial traders to take the long side of contracts, hedgers offer positive expected returns by setting futures prices

unique compilation of market data is a significant competitive advantage. . .. In addition, technical analysis is used to help manage trades."

below expected future spot prices.[13] In other words, financial traders require and earn a risk premium by providing price insurance.

The efficiency of this risk reallocation among traders hinges on there being a liquid marketplace to facilitate trading (Telser, 1981). Hedgers with a constant flow of commodities through their supply chains need to hedge continually rather than buy and hold (Grossman and Miller, 1988). Liquidity ultimately determines the markets' success (Cuny, 1993; Telser, 1981), as hedgers trade only in markets with sufficiently many counterparties to meet their demand. Several commodity futures contracts, such as those involving Pacific Northwest wheat (introduced in 1950), failed because they could not provide liquid hedges to meet hedgers' demand (Black, 1986; Working, 1953).[14]

Modern hedging pressure theory, however, posits that the markets' price insurance provision is not perfectly elastic and that risk sharing may be inefficient because market imperfections, such as capital constraints and informational frictions, can constrain liquidity and restrict financial traders' ability to bear risk (Hirshleifer 1988, 1990).[15] In particular, information asymmetries could undermine the supply of price insurance because traders would be reluctant to participate if they failed to fully understand a market's supply/demand characteristics (Hirshleifer,

[13] In this scenario, where futures prices are lower than expected future spot prices, futures prices are said to be in "normal backwardation"; otherwise, they are in "contango."

[14] As such, commodity futures markets embody many institutional features that make it highly liquid and minimize transaction costs for hedgers who have an elevated demand for immediacy. For example, commodity futures are traded on organized exchanges; since both buyers and sellers settle with the exchange's central clearing house and are subject to margin requirements, they face little counterparty risk. The standardization and fungibility of futures contracts and the large presence of market makers also significantly reduce transaction costs. The markets' capacity to sustain liquidity distinguishes them from other forms of market organizations; for instance, it makes futures markets accessible to individuals, like small farmers, who are unable to trade in over-the-counter derivatives markets dominated by institutions.

[15] Focusing on financial constraints, recent studies show that a deterioration in financial traders' risk-bearing capacity reduces the supply of price insurance and forces hedgers to carry more risk (Acharya et al., 2013; Cheng et al., 2015; Etula, 2013). Specifically, financial traders' investment losses in other assets can reduce their risk-absorption capacity and induce them to unwind positions in commodity futures, reducing the risk transferred from hedgers to financial traders (Cheng et al., 2015).

1990, 1988; Merton, 1987) and feared that other parties have an information advantage, e.g. some hedgers' generating private information through participating in physical commodities markets (Akerlof, 1970). These information asymmetries can be pervasive due to the globalization of commodities markets, which makes it difficult for less sophisticated traders to understand commodity supply, demand, and inventory. They are further exacerbated by the fact that insider trading restrictions have been absent for most of the markets' history (Verstein, 2016). As such, concerns over information asymmetry are widespread in practice. For instance, during the U.S. government shutdown in 2013, the temporary cessation of its commodity data publication program raised concern that some traders "may conclude the information asymmetry is too large and decide to scale back or not trade at all, severely curbing liquidity" (Kemp, 2013).

Empirical evidence of information asymmetries among market participants is also abundant. Focusing on energy futures markets from 1993 to 1997, Dewally, Ederington, and Fernando (2013) show that some traders exhibit superior information or skills and make persistent profits. In the corn futures market from 1995 to 2006, some hedgers are shown to have an information advantage pertinent to future price movements (Llorente and Wang, 2020). For a larger sample of 12 futures markets from 2000 to mid-2009, hedge funds and swap dealers are shown to possess private information (Fishe and Smith, 2012).

2.3 Theoretical Framework

Economic theories suggest that the impact of information disclosure on the pivotal risk-sharing function of these markets hinges on a central trade-off between two forces: the adverse-selection effect, where traders are reluctant to absorb risk when informationally disadvantaged, and the Hirshleifer effect, where it is impossible to transfer risk that has already been resolved. I borrow from Medrano and Vives's (2004) model and its application to the futures market in Vives (2010) to illustrate this trade-off.[16]

The model features a futures contract for a commodity with a future random spot price traded between three types of risk-averse traders: commodity producers, financial hedgers, and speculators. Commodity producers wish to hedge their production using futures after the production process has been set (e.g., after farmers have planted seeds). Financial hedgers, endowed with an asset with future random value correlated with the commodity's future spot price, trade futures to hedge their endowment shocks (e.g., hedge funds can trade futures to diversify their exposure in other assets, e.g., a stock index).[17] The third group—competitive uninformed speculators—trades futures to generate profits by absorbing the risks that producers and financial hedgers attempt to hedge.

Two regimes discussed by the authors are relevant to my study: (i) a private information regime in which the producer obtains a private signal about the future value of the commodity after the seeds have been planted but before trading occurs, and (ii) a public disclosure regime where the signal is available to all traders at the intermediate stage. In a setting with no public information about commodity fundamentals, trading reallocates risks from producers and financial hedgers to parties who are willing and able to bear them. In the private information regime, adverse selection discourages uninformed traders from sharing risks that producers and financial hedgers seek to hedge. Consequently, obtaining insurance via commodity futures is more expensive when private

[16] For more theories on the Hirshleifer effect in capital market settings, see for example, Alles and Lundholm (1993), Borocco (2017), Bushman (1991), Diamond (1985), Hakansson et al. (1982), and Verrecchia (2001, 1982).
[17] This way of modeling financial hedgers' hedging behavior can be found in recent theory on commodity futures markets, e.g., Goldstein and Yang (2022), and earlier literature, such as Easley et al. (2014), Han et al. (2016) and Wang (2015).

information reduces market depth. Less depth decreases the market's hedging effectiveness, leading risk-averse producers to cut their production *ex ante* as they obtain less price insurance.

When we introduce public information (through the public disclosure regime), this information mitigates adverse selection and increases risk-sharing opportunities by encouraging uninformed traders to share risks. At the same time, public information reduces insurance opportunities and producers' output through the Hirshleifer effect. The release of public information before trading occurs resolves some of the risk that traders attempt to hedge; the portion of risk resolved with information cannot be traded away, reducing the amount of risk that can be shared. At the extreme, if the public signal perfectly reveals the future value of the commodity, the futures price of the commodity adjusts to this future value. In this scenario, all risk is realized and borne by the parties who want to hedge but have yet to trade and no risk can be transferred to other parties through trading.[18] Therefore, producers and financial traders are worse off because of this detrimental risk-sharing effect (the latter because of revealed information correlated with their endowment shocks).

Several assumptions in Medrano and Vives (2004) and Vives (2010) are worth discussing. First, the authors assume that speculators are uninformed, whereas in practice some financial traders could generate private information about commodity fundamentals. As long as *some* traders are privately informed, regardless of their identities, public disclosure reduces information asymmetry, improves market depth, and encourages uninformed traders to participate and facilitate risk sharing (Diamond and Verrecchia, 1991).[19] Second, relatedly, information endowment is

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[18] Viewed differently, public information imposes additional risks on hedgers. As described by Hirshleifer (1971) and Verrecchia (1982), it "adds a significant distributive risk" and introduces "a lottery or an additional layer of uncertainty."
[19] Kyle (1985) notes that market depth is proportional to the ratio of noise trading to the private information informed traders are expected to have. Hence, public information can reduce informed traders' information advantage and improve market depth.

assumed to be exogenous; if costly private information collection is allowed, public information reduces traders' incentives to acquire private information and speculate *ex ante*, again generating better risk sharing (Diamond, 1985). These adverse-selection-reducing effects are expected to be large, given prior anecdotal evidence and research that suggests the presence of pervasive information asymmetries among commodity futures traders (see Section 2.2.1.).

The third assumption is that trading occurs after information is released. However, traders may trade to hedge risks prior to the arrival of information that resolves them. This argument is sometimes put forward to cast doubt on the Hirshleifer effect in financial markets that feature continuous trading. While theoretically sound, this argument may not apply in commodity futures markets (Marín and Rahi, 2000). In many cases, commodity futures do not provide a perfect hedge for traders' exposure because the price dynamics of the reference asset in a futures contract do not comove perfectly with the underlying risk to which traders are exposed (e.g., crude oil price vs. jet fuel price). Trading early may expose traders to extraneous risk in the reference asset and still result in inefficient risk sharing.

To summarize, public information improves risk sharing by alleviating adverse selection and encouraging more traders to accommodate the hedging demands of those endowed with suboptimal risk-sharing allocations. At the same time, information provision also inhibits risk transfer, with the outcome that traders cannot trade to optimal allocations and bear too much risk. Given this trade-off and the assumptions in the related theories, ultimately the effect of transparency on risk sharing is an empirical question.[20]

[20] The trade-off between the adverse-selection effect and the Hirshleifer effect has also been highlighted by economic theories in other capital market settings, such as Marín and Rahi (2000), who study market incompleteness, and Naik et al. (1999), who analyze public disclosure of trade details.

2.4 Related Literature

In addition to the theoretical research on the effect of information transparency on risk sharing in commodity futures markets discussed earlier, a broader literature investigates the role of information in commodity futures markets from other angles. This section reviews the related theoretical and empirical work.

2.4.1 Theories on the Role of Information in Commodity Futures Markets

In addition to the theories cited in Section 2.3. that speak to the risk-sharing impact of information in commodity futures markets, Eckwert and Zilcha (2003) study the general value of information in futures markets with the existence of a production economy. They analyze how the precision of public information about the future state of an asset affects the welfare of risk-averse agents. These agents' welfare depends on the risky future state, and they can hedge their exposure to the future state by trading futures. The authors distinguish between two types of information: information about non-tradable risk (risk that cannot be insured with futures) and information about tradable risk (risk that can be insured with futures). The former helps agents with their resource allocation decisions and therefore increases welfare. The latter has an ambiguous effect on welfare. It reduces the scope of risk that can be insured (the Hirshleifer effect) but also improves resource allocation. When agents are sufficiently risk-averse, the Hirshleifer effect dominates, and welfare decreases in the precision of information.

Kanodia et al. (2000) also study the role of information in futures markets with a production economy; instead of examining information about asset fundamentals, they focus on hedge accounting disclosures that provide information about firms' underlying risk exposures. The authors show that hedge accounting disclosures, by revealing information about firms' hedging-motivated trades and their speculative trades respectively, make futures prices more informative.

Informative futures prices are shown to lead to more efficient production decisions and better risk sharing.

2.4.2 Empirical Studies on the Role of Information in Commodity Futures Markets

A large empirical literature assesses the value and impact of various information releases about commodity fundamentals in commodity futures markets. The USDA releases reports on a regular basis disclosing fundamental data about agricultural products, such as Prospective Plantings, Acreage, Crop Production, Crop Production Annual Summary, Grain Stocks, World Agricultural Supply and Demand Estimate (WASDE), Cattle on Feed, and Hogs and Pigs. Researchers' interest in the informational value of public agricultural information programs stems from the concern that private firms providing information and analyses of these markets may substitute for public programs (Just, 1983; Salin et al., 1998) and budgetary pressures faced by government agencies (Garcia et al., 1997; Lehecka, 2014).

Researchers generally assess the value of such information by examining futures market reactions to changes in USDA information, demonstrating that these reports contain informational value. Early studies document that futures markets react to the issuance of these reports as measured by an increase in daily price changes or volatility (e.g., Garcia et al., 1997; Isengildina et al., 2006; Lehecka, 2014; Summer and Mueller, 1989). Recent studies use intraday prices and find strong price reactions to these releases in the form of volatility spikes; they also find that the markets quickly incorporate the new public information (e.g., Adjemian and Irwin, 2018; Lehecka et al., 2014). Complementing these studies, Isengildina-Massa et al. (2008) show that the WASDE reports reduce volatility implied from options prices, which constitutes additional evidence that these reports provide valuable information to market participants.

Despite consistent evidence that such public fundamental information generates futures market reactions, there exist two issues in translating such market reactions to the economic value of information. First, for different commodities, the surprises of supply and demand fundamental news only account for a minor portion of the observed volatility in futures prices (Carter, 1999; Chou et al., 2016). Recent studies, such as Halova et al. (2014) and Karali et al. (2020), propose that previous estimates of the relationship between information surprises and prices suffer from measurement errors in market surprises. After correcting for such measurement errors, they document a significant increase in the explanatory power of fundamental news for prices. Second, current markets react promptly, typically within an hour, to any newly disclosed information (Adjemian and Irwin, 2018), and yet using intraday prices to measure price reactions can be problematic because futures prices may not move efficiently in short time windows (Garcia and Leuthold, 2004). Huang et al. (2021) overcome this challenge by using newly developed risk-premium measures to estimate the risk-adjusted profits that accrue to USDA information and show that during 2010-2020, USDA announcement surprises have economic value.

3. Baseline Analysis

3.1 Empirical Measures

3.1.1 Transparency of Commodity Fundamentals

To examine the relationship between commodity fundamentals transparency and the capacity of commodity futures markets to accommodate risk sharing, I develop a measure to capture the availability of public information on commodity fundamentals for a given commodity market (*Info_Transp*). Specifically, I rely on the ability of futures prices to predict future realizations of spot prices. This measure is based on the idea that commodity futures markets aggregate available information about a commodity's future supply and demand (Cox, 1976; Grossman, 1977; Roll, 1984). Available information is impounded in futures prices, rendering them more informative about future spot prices. As such, futures price informativeness reflects the amount of fundamental information from available public sources.

I measure *Info_Transp* as the adjusted R-squared from commodity-specific regressions of spot prices at contract expirations on futures prices. Intuitively, this R-squared, which has been used to measure information precision in other contexts (e.g., Chen et al., 2022), captures the proportion of uncertainty about future spot prices that is resolved by information impounded in futures prices. Therefore, the higher *Info_Transp*, the greater the quality and quantity of information available to traders.

For each commodity on day *D*, I obtain an adjusted R-squared from estimating Eqn. (1) using observations over a time window of 600 days up through day *D*,[21]

$$S_T^i = \alpha_0 + \alpha_1 F_d^i + \alpha_2 MAT_d^i + \varepsilon_T^i, \qquad (1)$$

[21] The results are robust to time windows of 450 days and 750 days.

where $d \in (D - 600,\ D)$. This specification follows the daily-horizon specification in Switzer and El-Khoury (2007). For a particular commodity on day *d*, a few futures contracts with different expiration dates (denoted by contract *i*) are traded on futures exchanges. F_d^i is the closing price of contract *i* on day d. S_T^i is the prevailing spot price of the commodity on day *T*, when contract *i* matures. MAT_d^i is the number of days until maturity for contract *i* as of day *d*, i.e., the number of days between day *d* and day *T*. Figure 1 illustrates this estimation of *Info_Transp*.

For each commodity I utilize all actively traded contracts. This choice provides two benefits. First, it provides sufficient power and variation to produce an accurate estimate of *Info_Transp*. Second, more importantly, because the contracts expire on different dates, each contract's price contains incremental information about movements in commodity fundamentals that capitalize on different horizons. Hence, *Info_Transp* not only summarizes the precision of information from heterogeneous sources across market participants but also comprehensively captures the degree of information transparency along the temporal dimension.

3.1.2 Price Impact of Hedging Pressure

To assess the capacity of commodity futures markets to fulfill hedgers' risk-sharing needs, I use the price impact of hedging pressure.[22] My focus on this measure is motivated by hedging pressure theory, which posits that the measure directly reflects the cost or difficulty with which hedgers obtain price insurance from commodity futures markets. Intuitively, hedgers need to provide a price concession to incentivize risk-averse financial traders to take the other side of their trades. The provision of price insurance by financial traders is not, however, perfectly elastic (as a result, e.g., of financial constraints, setup costs, and informational asymmetries). Therefore, to

[22] Hedging pressure refers to hedgers' net futures positions driven by hedging demand.

accommodate higher hedging demand, futures prices need to decrease, generating a futures risk premium, to induce financial traders to take the other side of the trade. The futures risk premium, namely the hedging cost paid to compensate financial traders, is thus positively driven by hedging pressure. When markets become more constrained in supplying price insurance, hedgers need to offer a larger premium, which manifests in an amplified price impact of hedging pressure.

Prior studies show that price impact indeed reflects the cost of obtaining price insurance. For example, Acharya et al. (2013) document that, when financial traders' risk tolerance and willingness to provide insurance are low, hedging demand has a larger impact on prices. The price impact of hedging pressure is thus a reasonable proxy for the extent (or cost) of price insurance provision.

The data I use to estimate the price impact of hedging pressure come from weekly Commitment of Trader (COT) reports provided by the CFTC. The COT reports provide aggregate trading-position data for three major trader types: commercials, noncommercials, and nonreportables. All of a trader's reported futures positions in a commodity are classified as commercial if the trader uses futures contracts in that commodity for hedging, as defined in CFTC Regulation 1.3, 17 CFR 1.3(z). Commercial traders include commodity producers, merchants, processors, users, and swap dealers. Noncommercials include managed money (hedge funds) and other reportables. Following the commodity futures literature, I deem commercials hedgers, noncommercials financial traders, and nonreportables small participants (Kang et al., 2020; Rouwenhorst and Tang, 2012). For each trader group, I observe their aggregate long and short positions on a weekly basis.

Using these data, I estimate the price impact of hedging pressure following the return prediction specification in Kang et al. (2020),

$$R_{c,t+1} = \alpha_c + \gamma_t + \beta_1 Hedging\_Pressure_{c,t} + \beta_2 Pos\_Chng\_Com_{c,t} + ControlVariables_{c,t} + \varepsilon_{c,t+1}, \quad (2)$$

where $R_{c,t+1}$ is the futures excess return (an empirical proxy of the futures risk premium) for commodity c in week $t+1$ (Tuesday to Tuesday). The sensitivity of $R_{c,t+1}$ to $Hedging\_Pressure_{c,t}$ (β_1) captures the price impact of commercials' hedging pressure, my measure of interest. $Pos\_Chng\_Com_{c,t}$ is commercials' net position changes from week $t-1$ to week t (i.e., $Pos\_Chng\_Com_{c,t} = \frac{netlong\ position_{c,t} - netlong\ position_{c,t-1}}{OI_{c,t-1}}$).

$Hedging\_Pressure_{c,t}$ is calculated as the average of the net short positions of commercials from week $t-51$ to week t scaled by the open interest in week t (i.e., $Hedging\_Pressure_{c,t} = \frac{\sum_{s=t-51}^{t} commercial\ netshort\ position_{c,s}}{52 \times OI_{c,t}}$). This calculation using a trailing average solves a long-standing challenge in the literature to empirically establish a link between hedging pressure and excess returns (Kang et al., 2020; Rouwenhorst and Tang, 2012). This challenge arises in part because hedgers' positions can vary for hedging motives or speculative motives, including liquidity provision to financial traders, yet the commonly used trader-position data from COT reports disclose only hedgers' total positions, which embed both components. Kang et al. (2020) posit a key difference between these two components: while hedging demand is likely to be stable from week to week and changes only when hedgers adjust their operations, financial traders' liquidity needs fluctuate at short-term horizons. As such, Kang et al. (2020) employ a trailing moving average of commercials' net short positions to capture the relatively stable change in the positions driven by hedging demand ($Hedging\_Pressure_{c,t}$).

As a by-product of following Kang et al.'s (2020) framework, I also estimate the extent of hedgers' liquidity provision to financial traders. Kang et al. (2020) propose and show that, when financial traders trade to demand liquidity, hedgers act as the main liquidity providers. In Eqn. (2), after controlling for changes in hedging pressure, the remaining short-term fluctuations in commercials' position changes ($Pos\_Chng\_Com_{c,t}$) consist primarily of trades by commercials to meet noncommercials' liquidity demand. The sensitivity of returns ($R_{c,t+1}$) to commercials' position changes ($Pos\_Chng\_Com_{c,t}$) (β_2) in Eqn. (2) is, therefore, the price impact of noncommercials' liquidity-motivated trades and measures the extent (or cost) of liquidity provision to financial traders.

3.2 Baseline Regression

To test my main hypothesis concerning how transparency of commodity fundamentals affects the capacity of commodity futures markets to provide price insurance, I add to Eqn. (2) the interaction terms between $Info\_Transp_{c,t}$ and both $Hedging\_Pressure_{c,t}$ and $Pos\_Chng\_Com_{c,t}$,

$$\begin{aligned} R_{c,t+1} = \alpha_c + \gamma_t + \beta_1 Hedging\_Pressure_{c,t} + \beta_2 Pos\_Chng\_Com_{c,t} \\ + \beta_3 Info\_Transp_{c,t} \times Hedging\_Pressure_{c,t} \\ + \beta_4 Info\_Transp_{c,t} \times Pos\_Chng\_Com_{c,t} + \beta_5 Info\_Transp_{c,t} \\ + ControlVariables_{c,t} + \varepsilon_{c,t+1}, \qquad (3) \end{aligned}$$

where $Info\_Transp_{c,t}$ is information transparency estimated with Eqn. (1) for commodity c as of the Tuesday of week *t*. $R_{c,t+1}$, $Hedging\_Pressure_{c,t}$, and $Pos\_Chng\_Com_{c,t}$ are defined in Section 3.1.

My main coefficient of interest, β_3, describes the association between the price impact of hedging pressure and information transparency. $\beta_3 > 0$ suggests that, when public signals are more precise, it becomes costlier for hedgers to obtain price insurance, whereas $\beta_3 < 0$ indicates otherwise. Although it is not central to my hypothesis, I also estimate β_4, which describes the association between the price impact of noncommercials' liquidity-motivated trades and information transparency, to determine whether the cost of liquidity provision by hedgers to financial traders also changes with the precision of public information.

I include commodity-fixed effects (α_c) to control for time-invariant commodity characteristics that affect futures returns and time-fixed effects (γ_t) that absorb macro-level factors affecting futures returns. Following Kang et al. (2020), I include futures basis ($B_{c,t}$) and past returns to control for the effects of carry and momentum on futures returns. Based on Hirshleifer (1988), I also control for priced idiosyncratic risk ($\hat{v}_{c,t}$) in commodity futures that drives futures returns. The calculations of these control variables are described in the Appendix. I estimate conservative Driscoll and Kraay (1998) standard errors that are robust to cross-sectional dependence, heteroscedasticity, and temporal dependence when the time dimension becomes large.[23]

3.3 Data Sample and Descriptive Statistics

I obtain commodity futures price data from Pinnacle Corp. Aggregate trader position data are obtained from the weekly COT reports provided by the CFTC. Following Kang et al. (2020), I construct a sample consisting of 26 major commodities traded on four North American exchanges (NYMEX, NYBOT, CBOT, and CME). My sample period is from 1994 through 2020.[24]

Table 1 presents summary statistics for the full sample. The average hedging pressure ($Hedging\_Pressure_{c,t}$) is 14%, which is close to that reported in Kang et al. (2020). The median futures excess return ($R_{c,t+1}$) is 0.005%. $Info\_Transp_{c,t}$ has a mean of 0.286, suggesting that, on

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[23] The results are robust to clustering at the commodity and week levels. I use Driscoll and Kraay (1998) standard errors for the main analyses because the sample includes only 26 commodities that are to be clustered. It is worth noting that clustered standard errors are only asymptotically consistent if the number of clusters is large (Wooldridge, 2010). The Driscoll and Kraay (1998) approach does not rely on an asymptotic assumption for the number of commodities and has been used by recent studies in financial economics published in top finance journals (e.g., Boons et al., 2020; Jank et al., 2021).

[24] I replicated Kang et al.'s (2020) main results using these data for their sample, i.e., 26 commodities over the period from 1994 through 2017.

average, about 29% of the variation in future prevailing spot prices is captured by the information reflected in futures prices. With a standard deviation of 0.229, $Info\_Transp_{c,t}$ exhibits substantial variation within the sample.

3.4 Baseline Results

My main hypothesis concerns the effect of information transparency on price insurance provision to hedgers. I test this hypothesis by estimating Eqn. (3). Table 2 presents the results. The analyses employ the price impact measures described in Section 3.2. Column (1) estimates Eqn. (2) and displays the baseline estimation without interactions with $Info\_Transp_{c,t}$, where futures excess return ($R_{c,t+1}$) is regressed on hedging pressure ($Hedging\_Pressure_{c,t}$) and position changes by commercials ($Pos\_Chng\_Com_{c,t}$). This follows the specification for Table 5 in Kang et al. (2020). Consistent with Kang et al. (2020), the results show that $Hedging\_Pressure_{c,t}$ and $Pos\_Chng\_Com_{c,t}$ are positively correlated with $R_{c,t+1}$, consistent with the existence of positive hedging cost and positive cost of liquidity provision to noncommercials. The coefficient estimates on $Hedging\_Pressure_{c,t}$, $Pos\_Chng\_Com_{c,t}$, and control variables are close to those reported in Kang et al. (2020). The coefficient of 0.330 (3.698) on $Hedging\_Pressure_{c,t}$ ($Pos\_Chng\_Com_{c,t}$) indicates that a within-unit one-standard-deviation increase in $Hedging\_Pressure_{c,t}$ ($Pos\_Chng\_Com_{c,t}$) (0.130 (0.040)) leads to a larger excess return ($R_{c,t+1}$) by 0.043 (0.148) percentage points.

Column (2) introduces the interactions with $Info\_Transp_{c,t}$. The coefficient on $Info\_Transp_{c,t} \times Hedging\_Pressure_{c,t}$ is positive and significant, suggesting that, on average, hedgers face elevated costs to obtain price insurance when information transparency increases. The economic magnitude is meaningful—a within-unit one-standard-deviation increase in $Info\_Transp_{c,t}$ (0.208) amplifies the price impact of commercials' hedging-motivated trades by

73% (=0.208*1.153/0.330). This estimate is comparable to the effect of financial traders' risk tolerance documented by Acharya et al. (2013), who show that a one-standard-deviation change in speculator risk tolerance is associated with a 50–75% change in the price impact of producers' fundamental hedging demand. The coefficient on $Info\_Transp_{c,t} \times Pos\_Chng\_Com_{c,t}$ is not statistically different from zero, suggesting that the markets' capacity to accommodate financial traders' trading needs is on average not significantly associated with the precision of public information. Taken together, the results reported in Table 2 indicate that information transparency is associated with a reduction in price insurance provision to hedgers.[25]

In the next analysis, I assess whether the reduction in the supply of price insurance manifests in traders' trading behavior. All else equal, when it becomes more difficult to obtain price insurance, commercials' trading activity should decrease. Noncommercials should also trade less if they become less active in providing price insurance. As such, I analyze how each trader group's propensity to trade varies with $Info\_Transp_{c,t}$. I use the propensity to trade measure ($PT_{c,t}$) from Kang et al. (2020), calculated as the sum of the absolute changes in the aggregate long and aggregate short positions of each trader group scaled by their total gross positions at the beginning of the week ($PT_{c,t} = \frac{abs(Long_{c,t} - Long_{c,t-1}) + abs(Short_{c,t} - Short_{c,t-1})}{Long_{c,t-1} + Short_{c,t-1}}$). Like the portfolio turnover rate for stock market investors, this measure captures trading intensity. I include lagged futures excess returns ($R_{c,t}$) to control for the differences in trading strategies, because Kang et al. (2020) show that noncommercials and commercials trade in opposite directions based on past returns. Noncommercials tend to follow momentum trading strategies, whereas commercials trade as contrarians.

[25] I conduct robustness tests by constructing price impact measures using $R_{c,t+2}$. The results are qualitatively similar.

The results reported in Table 3 Columns (1)–(3) show that, when markets become more transparent, all three trader groups—noncommercials, commercials, and nonreportables—trade significantly less frequently. A within-unit one-standard-deviation increase in $Info\_Transp_{c,t}$ (0.208) reduces *PT_NonComm*, *PT_Comm*, and *PT_Nonrep* by 0.33, 0.066, and 0.11, respectively, equivalent to 3%, 1%, and 2% of their unconditional sample means. Column (4) examines the ratio of $PT\_NonComm_{c,t}$ to $PT\_Comm_{c,t}$, i.e., noncommercials' propensity to trade relative to that of commercials. It shows that transparency is associated with a more significant decline in noncommercials' trading. This large exodus of financial traders takes away the price insurance they provide to hedgers, consistent with the previous finding that transparency is associated with an increase in the cost of price insurance. Overall, the results reported in this table point to a curtailment of trading alongside greater transparency, suggesting that more public information plausibly impairs traders' ability to share risks via futures, forcing them to pull out of the markets.

A concern regarding the main results is that $Info\_Transp_{c,t}$ may capture traders' private information acquisition, which increases information asymmetry and thereby amplifies the price impact of hedging pressure. My results are inconsistent with this possibility: if this were the case, $Info\_Transp_{c,t}$ would be positively associated with informed traders' propensity to trade, because informed traders would trade more intensively if they had more precise private information (Kim and Verrecchia, 1994; Kyle, 1985). In contrast, I find robust *negative* correlations between $Info\_Transp_{c,t}$ and the propensity to trade for all traders, which are consistent with the risk-sharing channel.

4. Evidence from the Launch of the Agricultural Market Information System (AMIS)

The evidence presented in Section 3 indicates that transparency is associated with less price insurance provision for hedgers and a decline in trading for all trader groups. In this section, I employ a difference-in-differences research design to strengthen causal inferences and shed light directly on the consequences of regulatory efforts by exploiting the AMIS introduction as a plausibly exogenous shock to public information about commodity fundamentals.

In 2011, the G20 established the AMIS to enhance market information for four major crops: wheat, maize (corn), rice, and soybeans. The AMIS is a publicly accessible online platform that produces and publishes crop supply-and-demand forecasts and market analyses. Its launch was motivated by the G20's conclusion that "a lack of reliable and up-to-date information on crop supply, demand, stocks, and export availability contributed to recent price volatility" (FAO, 2011), which could be ameliorated by providing richer market information and analysis to help producers, traders, consumers, and governments make better decisions, avoiding panic-driven price surges.

The AMIS launch provided a wealth of information about market fundamentals for the affected crops. One of the AMIS's main outputs is a database of up-to-date market information on the historical and *forecasted* production, utilization, stockholding, and trade of the food crops. The database offers country-specific information for each of the 28 participants (with the EU representing all its member states, including individual G20 members) who compose roughly 80–90% of the targeted crops' global production; moreover, information about the rest of the world is provided in aggregate. Based on these data, the AMIS prepares and distributes a monthly market bulletin (called the "AMIS Market Monitor") that provides detailed analyses of global supply and demand, crop conditions, policy developments, and price trends in global food markets. A 2020 survey conducted by the Food and Agriculture Organization of the United Nations suggested that various parties, including commercial corporations, trade organizations, and public administrators, use the data to guide resource allocation decisions. Prior to the AMIS launch, they had to collect and compile the information themselves. Hence, the AMIS should have effectively enriched market information about the affected crops' fundamentals and can be used as a valid shock to the availability of such information.

Consistent with this conjecture, Figure 2 shows that only the commodities affected by the AMIS experience an increase in futures price informativeness while the other commodities exhibit a slight decrease in price informativeness. The figure plots the average futures price informativeness (*Info_Transp*) for affected crop commodities and the other commodities for the time periods before and after the AMIS launch.[26, 27] *Info_Transp* is estimated over a time window $d \in (D-300,\ D+300)$ following Eqn. (1). For crop commodities, futures price informativeness increases from 27% to 45%, representing a 67% increase. As commodity futures markets aggregate available information about future commodity fundamentals (Cox, 1976; Roll, 1984), this result suggests that all else equal, the AMIS launch enhances available public information for affected commodities. At the same time, the commodities that are not affected experience a decline in price informativeness from 38% to 33%. These results support my use of the AMIS setting as a

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[26] The commodities affected by the AMIS include corn, wheat, KC wheat, Minn wheat, soybeans, rough rice, soybean oil, and soybean meal. The 18 unaffected commodities include platinum, palladium, silver, copper, gold, oats, cotton, orange juice, lumber, cocoa, sugar, coffee, lean hogs, live cattle, feeder cattle, crude oil, heating oil, and natural gas.

[27] Pre-AMIS (post-AMIS) period is the period before (after) the AMIS launch date, i.e., September 2011. I estimate $Info\_Transp_{c,t}$ over a time window of 600 days centered around time *t*. As such, these periods exclude observations falling in the 600-day window around September 2011 to ensure that the data points used to estimate $Info\_Transp_{c,t}$ fall under the old and new regimes, respectively. The sample used to construct Figure 2 includes data up to 2 years before and 2 years after the shock. Consistent with the later analyses, the sample spans from March 2009 to March 2015.

meaningful shock that increases the availability of public information about commodity fundamentals impounded in futures prices for only affected commodities.

4.1 Main Analysis: Price Impact and Propensity to Trade

To examine my main hypothesis regarding the supply of price insurance, I implement a difference-in-differences (DiD) design to test whether the treatment commodity markets that received a positive information shock experienced differential changes in the price impact of hedging pressure around the shock relative to the unaffected commodity markets. I augment Eqn. (2) as follows:

$$
\begin{aligned}
R_{c,t+1} = \alpha_c + \gamma_t + \beta_1 Treat_c \times Post_t + \beta_2 Hedging\_Pressure_{c,t} \\
+ \beta_3 Treat_c \times Hedging\_Pressure_{c,t} + \beta_4 Hedging\_Pressure_{c,t} \times Post_t \\
+ \beta_5 Treat_c \times Post_t \times Hedging\_Pressure_{c,t} \\
+ \beta_6 Treat_c \times Pos\_Chng\_Com_{c,t} + \beta_7 Pos\_Chng\_Com_{c,t} \times Post_t \\
+ \beta_8 Treat_c \times Post_t \times Pos\_Chng\_Com_{c,t} + \beta_9 Pos\_Chng\_Com_{c,t} \\
+ ControlVariables_{c,t} + \varepsilon_{c,t+1}, \qquad (4)
\end{aligned}
$$

where $R_{c,t+1}$, $Hedging\_Pressure_{c,t}$, $Pos\_Chng\_Com_{c,t}$, and the control variables are defined in Section 3. $Treat_c$ is an indicator variable that equals 1 for 8 commodities that were affected by the shock and 0 for the other 18 commodities that were unaffected by the shock. For the estimation sample, I drop the year of the shock centered on the event date (September 2011) and include data up to 2 years before and 2 years after the shock. The calculation of $Hedging\_Pressure_{c,t}$ requires rolling 52 weeks of data, and thus post-shock observations start from April 2013 and continue until March 2015. The pre-shock data span March 2009 through February 2011. The specification includes commodity-fixed effects (α_c) and time-fixed effects (γ_t) to ensure that the treatment effect is estimated based on variation within a given commodity, after adjusting for the effects of macro-level time-varying shocks. Standard errors are computed following Driscoll and Kraay (1998) and are robust to heteroscedasticity as well as cross-sectional and time-series dependence.

My main coefficient of interest in Eqn. (4) is β_5, which measures changes in the price impact of hedging pressure of treatment commodities around the shock relative to the contemporaneous changes in that of the control commodities. $\beta_5 < 0$ indicates that the cost of price insurance decreases after the shock, whereas $\beta_5 > 0$ suggests otherwise. I also estimate β_8 to explore how the cost of liquidity provision by hedgers to financial traders changes around the shock.

Table 4, Panel A presents summary statistics for the full sample. The average hedging pressure ($Hedging\_Pressure_{c,t}$) is 14.2%. The median futures excess return ($R_{c,t+1}$) is 0.1%. The characteristics of the sample of observations around the AMIS launch do not differ significantly from those in the broader baseline sample described in the previous section. In particular, the summary statistics for hedging pressure ($Hedging\_Pressure_{c,t}$) and commercials' position changes ($Pos\_Chng\_Com_{c,t}$) are close to those of the baseline sample reported in Table 1.

Panel B reports the pre-treatment comparisons of control and treatment commodities. The treatment and control commodities show statistically significant differences for some variables. Commercials' hedging pressure ($Hedging\_Pressure_{c,t}$) is lower for treatment commodities (0.083) than for control commodities (0.17). Futures excess return ($R_{c,t+1}$) for treatment commodities (0.452%) is also lower than that for control commodities (0.576%). Commercials' position changes ($Pos\_Chng\_Com_{c,t}$) for the treatment and control commodities are not statistically different. Noncommercials have a greater propensity to trade for treatment commodities (7.393) than for control commodities (6.528). Given that treatment and control commodities differ along some dimensions, I assess the parallel trend assumption in greater detail in Section 4.2.

Table 5, Panel A presents the results of my main analysis regarding the effects of the AMIS on commodity futures markets' capacity to meet commercials' hedging needs. The analysis employs the price impact measure described in Section 3 and estimates Eqn. (4). The positive and significant coefficient on $Treat_c \times Post_t \times Hedging\_Pressure_{c,t}$ indicates an increase in the price impact of hedging pressure after the AMIS launch, suggesting that the affected crop markets offer less price insurance when the AMIS increases the precision of public information. The coefficient estimate on $Treat_c \times Post_t \times Hedging\_Pressure_{c,t}$ (3.885) indicates that the price impact of a within-unit one-standard-deviation-change in hedging pressure (0.086) increases by 0.334% (equivalent to 10% of the standard deviation of $R_{c,t+1}$) for treatment commodities relative to control commodities around the shock. The coefficient on $Treat_c \times Post_t \times Pos\_Chng\_Com_{c,t}$ is insignificantly different from zero, suggesting that the markets' capacity to provide liquidity to noncommercials is on average unlikely to be affected. Taken together, these results indicate that more precise public information via the AMIS reduces price insurance provision to commercials.[28]

To further attribute the price-insurance-reducing effect for hedgers to the provision of information by the AMIS, I perform a cross-sectional test by partitioning the treatment sample based on the extent of changes in $Info\_Transp_{c,t}$ around the shock. If the effect is driven by an increase in transparency, it should be stronger in markets that experience greater increases in $Info\_Transp_{c,t}$. Table 5, Panel B, shows that the result is consistent with this conjecture. For markets that underwent an above-sample-median increase in $Info\_Transp_{c,t}$, greater transparency

[28] I conduct robustness tests by constructing price impact measures using $R_{c,t+2}$. The results are qualitatively similar.

generated by the AMIS significantly reduces the price insurance obtained by commercials; the price-insurance-reducing effect is not statistically significant for markets that are less affected.

Next, I examine how each trader group's propensity to trade changes after the AMIS launch. Table 6 presents the results for the propensity of noncommercials (Column (1)), commercials (Column (2)), and nonreportables (Column (3)) to trade. For noncommercials and commercials, the coefficients on $Treat_c \times Post_t$ are significantly negative, indicating that these traders become less active when the AMIS increases the precision of public information. The coefficient of -1.119 (-0.429) on $Treat_c \times Post_t$ in Column (1) (Column (2)) implies that noncommercials' (commercials') propensity to trade reduces by -1.119 (-0.429) or 22% (15%) of the standard deviation of $PT\_NonComm_{c,t}$ ($PT\_Comm_{c,t}$) after the AMIS launch. Column (4) shows that noncommercials reduce their trading more than commercials, although the difference is not statistically significant.

Collectively, the evidence obtained from the AMIS shock lends additional support to the inference that treated markets experience an increase in the availability of public information following the AMIS launch and, as a result, supply less price insurance to commercials.

4.2 Identification Assumption

The validity of a difference-in-differences design relies on the key parallel trends assumption that, in the absence of treatment, the treatment and control groups should behave similarly regarding outcome variables. In this setting, both treatment and control futures markets are for major commodities; are actively traded; and face the same exposure to key macroeconomic factors that determine the supply of price insurance, such as shocks from the financial sector. Furthermore, as shown by Figure 1 in Tang and Xiong (2012) and Figure 1 in Cheng and Xiong (2014), commodities across both treatment and control sectors experienced similar changes in price volatility in the years leading up to 2011. The key difference is that the treatment markets experienced an information shock. Accordingly, it is reasonable to assume that in the absence of the treatment, these markets would behave similarly. Empirically, I estimate the dynamic change in the price impact of hedging pressure and show that treatment and control commodities track each other closely in the two years prior to the shock and exhibit divergence in trends only after AMIS increases the precision of public information. This suggests that it is unlikely that the parallel trends assumption is violated (Figure 3).

Although there is evidence to support the assumption of parallel trends prior to the AMIS launch, it is possible that treatment markets are affected by confounding factors that are concurrent with the shock. In particular, most of the treatment commodities are part of a commodity index, and these index commodities experienced a significant inflow of financial investors beginning in 2004, also known as the financialization of commodity markets. Although my sample begins after the financialization period (2004–2008), one might be concerned that the treatment and control commodities continued to receive different levels of interest from index investors. This concern is mitigated by the fact that seven of eight treatment commodities (all except rice) are listed in indices, while treatment commodities overall experienced a *decrease* in financial traders' propensity to trade. To further address the concern that my results may be affected by the financialization of commodity markets, I include only index commodities in the control group that are expected to receive the same interest from financial investors as the treatment group. The results (untabulated) remain unchanged. Furthermore, to alleviate any concern that there may be unobservable heterogeneity between agricultural and non-agricultural commodities, I use only unaffected *agricultural* commodities as the control group and document similar results (untabulated).

5. Evidence of the Hirshleifer Effect Channel

In this section, I present analyses that shed light on the mechanisms underlying my main results and assess whether the documented effects are due to reduced risk sharing opportunities (i.e., the Hirshleifer effect channel).

5.1 Sensitivity of Hedging Positions to Fundamental Hedging Demand

I first examine how the sensitivity of hedgers' hedging positions to their fundamental hedging demand changes around the AMIS launch. If the greater transparency facilitated by the AMIS reduces risk sharing opportunities, I should observe a drop in hedgers' hedging level relative to their fundamental hedging demand after the AMIS launch.

I measure hedgers' aggregate fundamental hedging demand at the commodity level using their aggregate default risk. Empirical and analytical studies on corporate risk management suggest that corporate hedging demand is driven by managerial aversion to distress and default (e.g., Stulz, 1984); a firm increases hedging demand as its likelihood of distress and default increases. I follow Acharya et al. (2013) and use the Zmijewski (1984) score calculated from Compustat data as a proxy for individual firm-level default risk and aggregate this score at the commodity-quarter level. The Appendix discusses the details of the construction of the aggregate default risk measure (*Def_Risk*). Because default risk is measured using Compustat data on a quarterly basis, I measure hedgers' hedging positions using the average hedging pressure in a given quarter (*Hedging_Pressure*). Thus, the sample for this test is formed at the commodity-quarter level. Table 7, Panel A presents the results and shows that the sensitivity of hedgers' hedging positions to aggregate corporate default risk, as indicated by the coefficient on $Def\_Risk_{c,q-1} \times Treat_c \times Post_q$, reduces around the AMIS launch, suggesting that for any given level of fundamental hedging demand the markets become less efficient at accommodating hedgers' hedging-motivated trades after the AMIS shock.

5.2 Risk Sharing for Financial Traders

Second, I examine how the responsiveness of financial traders' net trading to stock market downturns changes around the shock. If previously documented effects stem from a reduction in risk sharing opportunities, such a reduction should also affect financial traders' diversification-motivated trading, which is another form of risk sharing. Both commercial hedgers and those financial traders who trade for portfolio diversification can be conceived as using futures to hedge their exposure to another risky asset with payoffs correlated with that of futures—exposure to future commodity price movements for commercial hedgers and exposure to price movements of other assets for financial traders. The traders in general seek to insure against their idiosyncratic shocks with futures. If, for instance, a public signal reveals the future state of the shocks traders attempt to hedge against, futures price will reflect the future state immediately, making it impossible to use futures to insure against the shocks of interest. To the extent that information renders future states uninsurable, greater revelation of information by the AMIS also reduces the attractiveness of futures as a diversification tool.

Financial traders' diversification motives in trading futures are strong when the stock market is in distress. Chen et al. (2019) show that, during stock market downturns, hedge funds investing in commodity futures provide their investors with significant diversification benefits, which in turn drive investor inflows. I examine financial traders' inflows to futures markets during stock market downturns to infer the capacity of the markets to accommodate their diversification needs. Following Chen et al. (2019), I define periods of stock market distress (*SP500_5pct*) as weeks in which the weekly average S&P 500 index return falls within the lowest 5^{th} percentile of its entire history.[29] Table 7, Panel B shows that after AMIS, financial traders' net inflows to affected futures markets decrease during stock market downturns relative to other periods (as indicated by the coefficient on $SP500\_5pct_t \times Treat_c \times Post_t$), suggesting that the affected agricultural futures become less appealing to financial traders seeking diversification benefits. Overall, the evidence reported in Table 7 points to a loss of risk sharing potential for both hedgers and financial traders after AMIS.

5.3 Cross-Sectional Analysis

To further corroborate the risk sharing story, I examine the factors underlying the documented increase in price impact around the AMIS launch. Economic theory on risk sharing suggests that the adverse risk-sharing effect should be stronger when traders can better hedge their risks *ex ante* (Eckwert and Zilcha, 2003). I investigate whether the price impact result is modulated by the degree to which traders can share risks *ex ante*. I posit that risk sharing is easier when positions are held by a dispersed group of traders who are exposed to diverse idiosyncratic risks. Accordingly, I partition the treatment and control samples based on their respective median values of market position dispersion (*Market Position Dispersion*) in the pre-treatment period and examine the AMIS's effects on price impact for the two subsamples with high and low market position dispersion, respectively.

I measure the dispersion of market positions by taking advantage of the COT data on market concentration ratios. For each market the CFTC provides, on a weekly basis, the percentages of open interest held by the largest eight reportable traders without regard to whether they are classified as commercial or noncommercial. I calculate the average concentration ratio for net long

[29] The results are robust to defining the stress period as weeks in which the weekly average S&P 500 index returns fall more than two standard deviations below the average over its entire history.

and net short positions and multiply it by -1, so that larger values represent greater position dispersion. The intuition for this measure is that, if the largest traders hold larger market shares and are more dominant, it is more likely that traders' exposure to risks is correlated in aggregate, making it difficult for traders to trade risk-sharing instruments that insure against their exposure to idiosyncratic risks. This use of concentration ratios to assess risk-sharing conditions in commodity futures markets is new to the literature.

Consistent with this conjecture, the results reported in Table 8, as indicated by the difference in the coefficients on terms [a] and [b], show that the price insurance reduction for commercials is more pronounced in markets with greater market position dispersion.

6. Evidence of the Information Asymmetry Channel

As discussed in Section 2, economic theories suggest that greater disclosure of fundamentals can influence the extent of risk sharing by altering information asymmetry among market participants. In this section, I explore whether the information asymmetry channel also plays a role in shaping risk sharing. Specifically, I examine whether the effects of transparency on price impacts are functions of trader sophistication, a determinant of information asymmetry. I measure hedgers' and financial traders' sophistication by their average position sizes; traders with larger positions are likely to possess superior resources and skills with which to generate private information about commodity fundamentals.

Columns (1)–(3) of Table 9 present the results of the cross-sectional analyses based on financial trader sophistication, hedger sophistication, and disparity in trader sophistication in the pre-period, respectively.[30] Columns (2) and (3) show that the adverse risk-sharing effect of transparency is alleviated in markets where hedgers are more sophisticated (in both absolute and relative terms, as indicated by the coefficient on term [a] in Column (2) and that on term [b] in Column (3)), but the differences in the effects between the subsamples are not statistically significant (as indicated by the differences in the coefficients on terms [a] and [b]). This finding suggests that the classical adverse-selection-reducing effect of public information is likely at play but immaterial—public information via the AMIS potentially reduces hedgers' information advantage and information asymmetry, rendering financial traders more willing to provide price insurance.

[30] Disparity in sophistication is measured as the signed difference between noncommercials' average position size and that of commercials.

Moreover, Column (3) suggests that AMIS improves the markets' capacity to accommodate financial traders' trading in markets where they are more sophisticated than hedgers (as indicated by the differences in the coefficients on terms [c] and [d]). Public information from the AMIS reduces financial traders' (hedgers') information (dis)advantage, making hedgers more willing to provide liquidity.

7. The SEC Revision of Oil and Gas Reporting Disclosures

Section 4.2 discusses the validity of the identification assumption for the AMIS setting and different ways to address concerns over the identification assumption. To further mitigate concerns about endogeneity, I employ an information shock to a different sector at a different time—the revision of the SEC annual oil and gas (OG) reporting disclosures under Regulation S-K and Regulation S-X in 2009, which arguably increases the availability of public information about future oil and gas supply. The revision introduced bright-line probability thresholds to the estimation of oil and gas reserves, with the intent "to provide investors with a more meaningful and comprehensive understanding of oil and gas reserves" (Securities and Exchange Commission 2009). Badia et al. (2020) find that the new reserve estimates are associated with decreases in the bid–ask spreads of stock prices and are more closely related to stock price changes, suggesting that they provide more precise information about the volumes and development of the reserves. Moreover, the regulation required detailed disclosures about reserves that enable market participants to assess the volumes and development of those reserves more accurately. These more precise reserve disclosures, when issued by all public oil and gas companies, would collectively provide a better signal of the volumes of oil and gas that can be reasonably extracted and the reserves' development progress and, hence, future oil and gas supply from these reserves.[31]

I use this setting and conduct difference-in-differences analyses to examine whether the oil and gas markets that experience an increase in the availability of fundamental information exhibit differential changes in the price impact of hedging pressure and traders' propensity to trade around

[31] An added advantage of this setting is that the reform is intended to ensure that the SEC reporting requirements reflect technological changes in the petroleum industry and facilitate equity investors' valuation of oil and gas companies and therefore are largely exogenous to futures market participants' demand for information.

the regulation change relative to unaffected commodity markets. Table 10 presents the results for the analysis of price impact by estimating Eqn. (4). Consistent with the sample in the AMIS setting, I drop the event year (year 2009) and include data up to 2 years before and 2 years after the shock. Because the estimation of *Hedging_Pressure* requires rolling 52 weeks of data, the post-shock observations start from January 2011 and continue until December 2012. The pre-shock data span January 2007 through December 2008. *Post* is an indicator variable that equals 1 for periods after 2009 and 0 otherwise. The treatment markets are those for oil and gas commodities, including crude oil, heating oil, gasoline, and natural gas. As gasoline is one of the major outputs of oil and gas companies, the regulation change is expected to significantly impact the availability of information that aids the forecast of gasoline supply. As such, gasoline is included in the treatment group for analysis. *Treat* is an indicator variable that equals 1 for crude oil, heating oil, gasoline, and natural gas and 0 for the other 15 commodities unaffected by this shock and the AMIS launch.[32] The regression model includes the same set of controls as in prior analyses and commodity and time-fixed effects, while standard errors are computed following Driscoll and Kraay (1998). Table 10 shows a positive and significant coefficient on $Treat_c \times Post_t \times Hedging\_Pressure_{c,t}$, suggesting that the affected oil and gas markets experience an increase in the price impact of hedging pressure when the SEC regulation change increases the availability of public information. This analysis provides inferences consistent with those obtained from the baseline analysis and the analysis using the AMIS setting.

Table 11 presents the results for the analysis of traders' propensity to trade (Column (1) for noncommercials, column (2) for commercials, column (3) for nonreportables, and column (4)

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[32] The 15 unaffected commodities include platinum, palladium, silver, copper, gold, oats, cotton, orange juice, lumber, cocoa, sugar, coffee, lean hogs, live cattle, and feeder cattle.

for the ratio of noncommercials' propensity to trade over that of commercials'). Columns (1), (3), and (4) show negative and significant coefficients on $Treat_c \times Post_t$, indicating that noncommercials and nonreportables reduce their propensity to trade around the SEC regulation change and that noncommercials reduce their propensity to trade more than commercials. These results are qualitatively similar to those from prior analyses and consistent with greater information introduced by the SEC regulation change makes it harder for traders to share risks via futures. However, the coefficient on $Treat_c \times Post_t$ in column (2) is not statistically significant from zero, suggesting that the regulation change has no discernible effect on commercials' propensity to trade. As commercials' propensity to trade captures their trading driven by different motives, it is possible that I might not detect a decrease in propensity to trade even if commercials' ability to share risks via the markets declines. This could be the case if, for example, greater information provision reduces noncommercials' information advantage and motivates more commercials to trade to provide liquidity.

Next, I perform further analyses to investigate whether the increase in hedging cost and decline in trading around the SEC regulation change are driven by reduced risk sharing opportunities. In Table 12, I examine how the sensitivity of hedgers' hedging positions to their fundamental hedging demand changes around the SEC regulation change. I adopt the same empirical design as in Table 7, Panel A. The negative and significant coefficient on $Def\_Risk_{c,q-1} \times Treat_c \times Post_q$ suggests that the sensitivity of hedgers' hedging positions to fundamental hedging demand, as proxied by aggregate corporate default risk, reduces around the SEC regulation change, consistent with the markets becoming less efficient at accommodating hedgers' hedging demand after the change.

In Table 13, I examine how the responsiveness of financial traders' net trading to stock market downturns changes around the SEC regulation change. I adopt the same empirical design as in Table 7, Panel B. The negative and significant coefficient on $SP500\_5pct_t \times Treat_c \times Post_t$ suggests that after the regulation change, financial traders' net inflows to affected futures markets decrease during stock market downturns relative to other periods, consistent with the affected markets becoming less appealing to financial traders seeking diversification benefits. The results in Tables 12 and 13 collectively reveal a loss of risk sharing potential for both hedgers and financial traders after the regulation change.

8. Conclusion

While policymakers in commodity markets generally believe that greater transparency is desirable, its effect on the markets' key risk-sharing function is unclear. Consistent with policymakers' preference for transparency to enable market participants to make more informed resource allocation decisions (IOSCO, 2008), this study shows that greater public disclosure (e.g., via the AMIS) improves price discovery in futures markets, which helps guide economic decision-making. At the same time, my results yield the first empirical evidence that increasing the transparency of commodity fundamentals has costs: it results in lost risk sharing opportunities for both hedgers and financial traders by hindering the flow of risk to parties that can most efficiently bear it. Hedgers end up holding more risk and facing heightened hedging costs than they would otherwise. Information transparency may also improve risk sharing by reducing information asymmetries, but this effect is not as consequential. Overall, this paper highlights the downside of increasing transparency in markets where risk sharing is particularly important.

This study is not intended to provide a complete cost–benefit analysis of regulatory efforts to increase transparency by quantifying their net benefits (or costs). I adopt an alternative approach and show how the detrimental risk-sharing effect and the beneficial adverse-selection effect vary with market characteristics, e.g., dispersion of market positions and trader sophistication. These findings suggest that policymakers may consider the characteristics of individual commodity markets to determine the optimal level of transparency. My findings also shed light on the particular markets where transparency may be more or less costly. An avenue for future research is to extend this study and analyze the real effects of transparency on commodity firms' hedging, financing, and investment decisions, as risk management theory suggests that changes in hedging efficacy influence production and investment efficiency. Such analyses would be fruitful for gaining an understanding of the net effects of transparency on the real sector.

Appendix A: Variable Definitions

Variable	Definition	Source
$\boldsymbol{Info\_Transp_{c,t}}$	$Info\_Transp_{c,t}$ is futures price informativeness estimated following Eqn. (1) for commodity *c* as of the Tuesday of week *t*. I estimate the panel regression from Eqn. (1) below for each commodity for day *D* using observations over a time window of 600 days prior to day *D*. $S_T^i = \alpha_0 + \alpha_1 F_d^i + \alpha_2 MAT_d^i + \varepsilon_T^i,$ (1) where $d \in (D-600,\ D)$. For a particular commodity, on each day *d*, a number of contracts expiring on different dates are traded on futures exchanges. F_d^i is the futures price of contract *i* on day *d*. S_T^i is the prevailing spot price of the commodity on day *T*, when contract *i* matures. MAT_d^i is the number of days for contract *i* to mature as of day *d*, i.e., the number of days between day *d* and day *T*. Figure 1 provides an illustration of this calculation for *Info_Transp*.	Datastream, FactSet, Pinnacle Corp.
$\boldsymbol{R_{c,t}}$	Weekly excess returns (Tuesday to Tuesday) for commodity *c* in week *t* calculated using the front-month contract (in %), $R_{c,t} = \frac{F_c(t,T) - F_c(t-1,T)}{F_c(t-1,T)}$ where $F_c(t,T)$ is the futures price at the end of week *t* for the front-month contract maturing on date *T*. For weeks ending before the seventh calendar day of the month, the front contract is defined as the closest-to-maturity contract available, including those that expire in the current calendar month. For weeks ending on or after the seventh calendar day, the front month is defined as the closest-to-maturity contract expiring after the current calendar month. If the seventh day is not a business day, the next business day is considered as the cutoff date.	Pinnacle Corp.
$\boldsymbol{Pos\_Chng\_Com_{c,t}}$	Net trading of commercials for commodity *c* in week *t*. Defined as the net purchase of futures contracts by commercials. Calculated as the change in commercials' net long position in commodity *c* between weeks *t-1* and *t*, scaled by lagged open interest. $Pos\_Chng\_Com_{c,t} = \frac{netlong\ position_{c,t} - netlong\ position_{c,t-1}}{OI_{c,t-1}}$	COT reports
$\boldsymbol{Hedging\_Pressure_{c,t}}$	Hedging pressure for commodity *c* in week *t*. Calculated as the trailing 52-week moving average of the net short positions of commercials from week *t-51* to week *t* divided by the open interest in week *t*: $Hedging\_Pressure_{c,t} = \frac{\sum_{s=t-51}^{t} commercial\ netshort\ position_{c,s}}{52 \times OI_{c,t}}$	COT reports
$\boldsymbol{PT\_Comm_{c,t}}$	Commercials' propensity to trade for commodity *c* in week *t*. Calculated as the sum of the absolute changes in the aggregate long and	COT reports

	aggregate short positions of commercials, scaled by their lagged total gross positions: $$PT_{c,t} = \frac{abs(Long_{c,t} - Long_{c,t-1}) + abs(Short_{c,t} - Short_{c,t-1})}{Long_{c,t-1} + Short_{c,t-1}}$$	
$\boldsymbol{PT\_NonComm_{c,t}}$	Noncommercials' propensity to trade for commodity *c* in week *t*. Calculated as the sum of the absolute changes in the aggregate long and aggregate short positions of noncommercials, scaled by their lagged total gross positions: $$PT_{c,t} = \frac{abs(Long_{c,t} - Long_{c,t-1}) + abs(Short_{c,t} - Short_{c,t-1})}{Long_{c,t-1} + Short_{c,t-1}}$$	COT reports
$\boldsymbol{PT\_Nonrep_{c,t}}$	Nonreportables' propensity to trade for commodity *c* in week *t*. Calculated as the sum of the absolute changes in the aggregate long and aggregate short positions of nonreportables, scaled by their lagged total gross positions: $$PT_{c,t} = \frac{abs(Long_{c,t} - Long_{c,t-1}) + abs(Short_{c,t} - Short_{c,t-1})}{Long_{c,t-1} + Short_{c,t-1}}$$	COT reports
$\boldsymbol{PT\_Ratio_{c,t}}$	$PT\_NonComm_{c,t}$ divided by $PT\_Comm_{c,t}$.	COT reports
$\boldsymbol{B_{c,t}}$	Log basis for commodity *c* in week *t*, $$B_{c,t} = \frac{\ln(F_c(t,T_2)) - \ln(F_c(t,T_1))}{(T_2 - T_1)/365}$$ where $F_c(t,T_1)$ and $F_c(t,T_2)$ are the prices of the closest and next-closest-to-maturity contracts for commodity *c* in week *t*.	Pinnacle Corp.
$\boldsymbol{\hat{v}_{c,t}}$	Annualized standard deviation of the residuals from a regression of commodity futures returns on S&P 500 returns (calculated using a 52-week rolling window) multiplied by $S_{c,t}$. $S_{c,t}$ is an indicator variable that equals 1 when noncommercials are net long and -1 when they are net short.	Pinnacle Corp.
$\boldsymbol{Hedging\_Pressure_{c,q}}$	Hedging pressure for commodity *c* in quarter *q*. Calculated as the average of the net short positions of commercials in quarter *q* divided by the open interest as of the last week in quarter *q*.	COT reports
$\boldsymbol{Def\_Risk_{c,q-1}}$	Average default risk for public firms with exposure to commodity *c* in quarter *q-1*. Default risk is measured using the Zmijewski (1984) score. I aggregate firm-specific Zmijewski (1984) scores within each commodity sector for each quarter using a weighted average based on the firms' total assets. Following Brogaard et al. (2019) and Ferracuti (2022), I determine a firm's exposure to a particular commodity by counting the number of instances that commodity is mentioned in the	Compustat, 10-K

	firm's Form 10-K annual report. A firm's Zmijewski (1984) score is included in the aggregation for a particular commodity if its average word count for that commodity is in the top decile of the sample average word counts for that commodity. Each firm's Zmijewski-score is calculated as $Zmijewski-score = -4.3 - 4.5 * NetIncome/TotalAssets + 5.7 * TotalDebt/TotalAssets - 0.004 * CurrentAssets/CurrentLiabilities$	
$\boldsymbol{Pos\_Chng\_NonComm_{[t,t+4]}}$	Net trading of noncommercials for commodity *c* in week *t+1* to week *t+4*. Defined as the net purchase of futures contracts. Calculated as the change in noncommercials' net long position in commodity *c* between weeks *t* and *t+4*, scaled by the open interest at the beginning of week *t+1*: $Pos\_Chng\_NonComm_{[t,\ t+4]} = \frac{netlong\ position_{c,t+4} - netlong\ position_{c,t}}{OI_{c,t}}$	COT reports
$\boldsymbol{SP500\_5pct_t}$	Equals 1 if the weekly average S&P 500 index returns fall in the lowest 5th percentile over its entire history and 0 otherwise.	WRDS
Market Position Dispersion	Market-level average concentration ratio multiplied by -1. The concentration ratio is the percentage of open interest held by the largest eight traders in each commodity market.	COT reports
Noncommercial (Commercial) Sophistication	Noncommercials' (commercials') average position size, calculated as noncommercials' (commercials') total positions divided by the number of noncommercial (commercial) traders.	COT reports
Disparity in Trader Sophistication	Signed difference between noncommercials' average position size and that of commercials.	COT reports

Appendix B: Main Tables and Figures

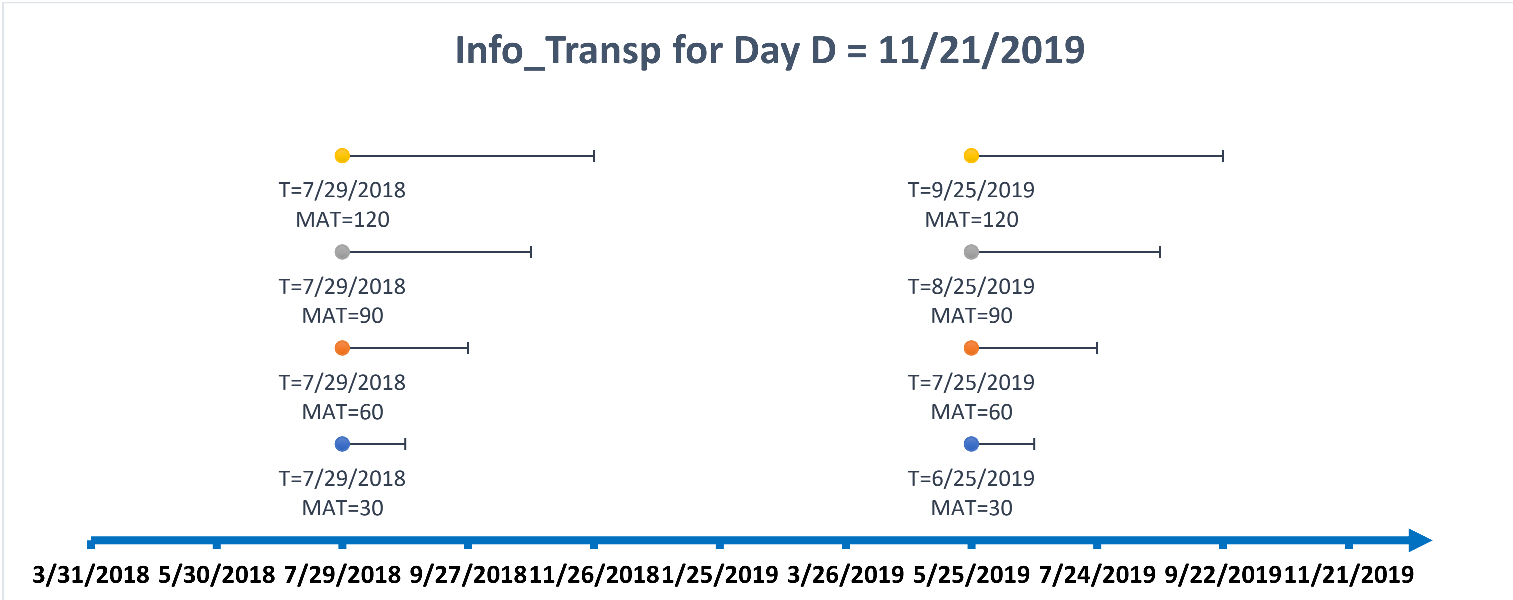

Figure 1: Example of *Info_Transp* Calculation

This figure illustrates the calculation of futures price informativeness (*Info_Transp*) for a particular commodity as of November 21, 2019 (*D* = 11/21/2019). This calculation estimates the ability of the futures prices falling within the 600-day window leading up to 11/21/2019 (i.e., 3/31/2018 to 11/20/2019) to predict spot prices on later contract expiration dates. The predictive ability is proxied by the adjusted R-squared of Eqn. (1).

$$S_T^i = \alpha_0 + \alpha_1 F_d^i + \alpha_2 MAT_d^i + \varepsilon_T^i, \qquad (1)$$

The unit of observation for estimating Eqn. (1) is the day-contract. Each regression includes the trading days falling within the 600-day window, i.e., $d \in (D - 600,\ D)$. On each trading day d, a few futures contracts with different expiration dates are traded on futures exchanges. For example, as the figure shows, on 7/29/2018 and 5/25/2019, respectively, four contracts are traded, each expiring in 30, 60, 90, or 120 days.

To illustrate the data structure, consider the four contracts traded on 5/25/2019. Each of the contracts (denoted by i) has a closing price on 5/25/2019 (F_d^i, d = 5/25/2019) that is expected to impound information about the future commodity spot price on the contract expiration date (S_T^i). For example, for the contract that expires in 30 days on 6/25/2019 (T = 6/25/2019, MAT = 30), its closing price on 5/25/2019 should be informative about the spot price on 6/25/2019 (S_T^i, T = 6/25/2019). Therefore, this closing price on 5/25/2019 and the spot price on 6/25/2019 would form the pair of data points for an observation used in estimating Eqn. (1).

Each of the eight contracts shown in the figure above constitutes an observation. All the contracts traded on each applicable trading day in the 600-day window are included for estimation. The adjusted R-squared of this regression then represents an aggregate degree of informativeness for futures prices falling within the 600-day window and therefore produces a stable estimate of the information intensity reflected in futures prices.

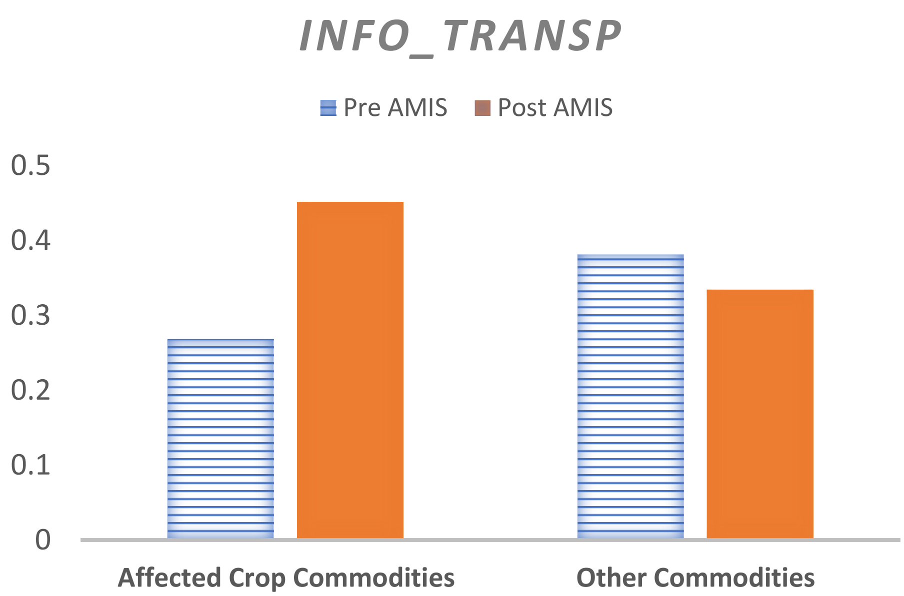

Figure 2: *Info_Transp* before and after AMIS Launch

The figure plots the average futures price informativeness (*Info_Transp*) for affected crop commodities and the other commodities for the time periods before and after the AMIS launch. *Info_Transp* is estimated over a time window $d \in (D - 300,\ D + 300)$ following Eqn. (1). Section 4 defines the affected crop commodities and the pre- and post-AMIS periods.

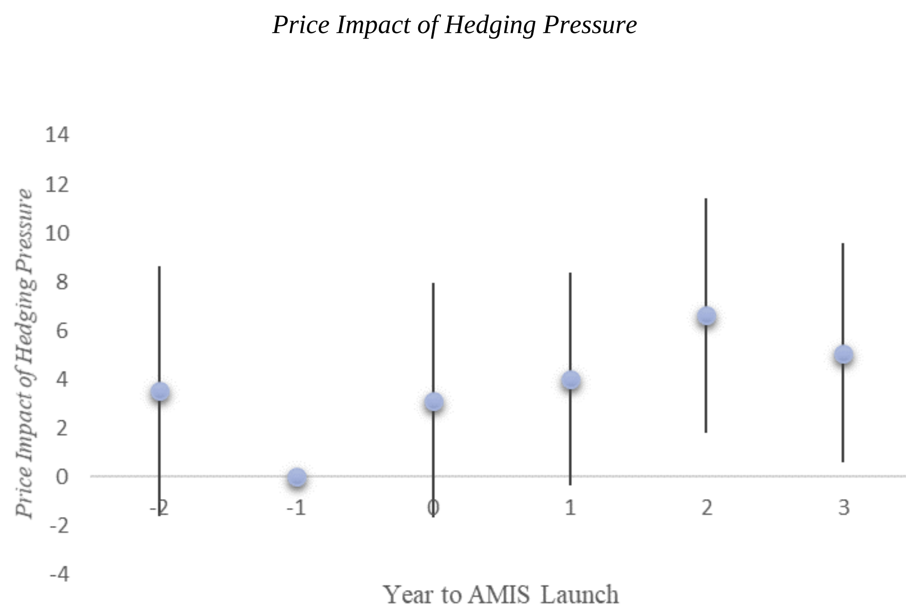

Figure 3: AMIS Parallel Trend

This figure displays the treatment effects estimated for each year as indicated on the x-axis with 95% confidence intervals for the price impact of hedging pressure. The treatment effects are estimated according to the difference-in-differences specifications with year indicators. All coefficients are estimated relative to the year prior to the event year.

Table 1: Baseline Sample Descriptive Statistics

This table presents the descriptive statistics for the main variables in the baseline sample. All variables are defined in the Appendix.

	(1) N	(2) Mean	(3) Std. Dev.	(4) P25	(5) P50	(6) P75
$R_{c,t+1}$ (in %)	31,493	0.064	3.743	-2.104	0.005	2.165
$Hedging\_Pressure_{c,t}$	31,493	0.139	0.192	0.003	0.103	0.245
$Pos\_Chng\_Com_{c,t}$	31,493	-0.001	0.043	-0.021	0.000	0.020
$Info\_Transp_{c,t}$	31,493	0.286	0.229	0.085	0.236	0.451
$PT\_NonComm_{c,t}$	31,462	9.513	9.359	3.565	6.526	11.836
$PT\_Comm_{c,t}$	31,462	4.769	3.797	2.129	3.718	6.213
$PT\_Nonrep_{c,t}$	31,462	6.781	5.537	3.052	5.290	8.648
$PT\_Ratio_{c,t}$	31,462	2.649	2.716	1.074	1.865	3.122
$B_{c,t}$	31,493	0.039	0.213	-0.009	0.041	0.123
$\hat{v}_{c,t}$	31,493	0.205	0.501	-0.310	0.385	0.552

Table 2: Baseline Regression – Information Transparency and Cost of Price Insurance

This table estimates the association between the degree of transparency and the price impact of hedging pressure. It presents OLS estimates of Eqs. (2) and (3). Column (1) replicates the specification for Table 5 in Kang et al. (2020), where commodity futures excess return (*R*) in week *t+1* is regressed on hedging pressure (*Hedging_Pressure*) and commercial hedgers' position changes (*Pos_Chng_Com*) in week *t*. Column (2) examines how the price impacts of hedging pressure (*Hedging_Pressure*) and commercial hedgers' position changes (*Pos_Chng_Com*) vary with the degree of transparency (*Info_Transp*). All columns include control variables. *Info_Transp* and control variables are measured as the deviation from their respective sample means. All variables are defined in the Appendix. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity as well as cross-sectional and temporal dependence are reported in parentheses. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

	(1) $R_{c,t+1}$	(2) $R_{c,t+1}$
$Hedging\_Pressure_{c,t}$	0.330*	0.226
	(1.743)	(1.158)
$Pos\_Chng\_Com_{c,t}$	3.698***	3.711***
	(6.141)	(6.105)
$\boldsymbol{Info\_Transp_{c,t} \times Hedging\_Pressure_{c,t}}$		**1.153****
		(2.511)
$Info\_Transp_{c,t} \times Pos\_Chng\_Com_{c,t}$		0.918
		(0.451)
$Info\_Transp_{c,t}$		0.016
		(0.116)
$B_{c,t}$	-0.238	-0.249*
	(-1.642)	(-1.721)
$\hat{v}_{c,t}$	-0.112*	-0.102*
	(-1.825)	(-1.651)
$R_{c,t}$	2.857***	2.803***
	(2.902)	(2.855)
Commodity FE	Y	Y
Year-week FE	Y	Y
Observations	31,493	31,493
Adjusted R-squared	0.178	0.178

Table 3: Baseline Regression – Information Transparency and Propensity to Trade

This table estimates the association between the degree of transparency and traders' propensity to trade. The dependent variable is noncommercial financial traders' propensity to trade (*PT_NonComm*) for column (1), commercial hedgers' propensity to trade (*PT_Comm*) for column (2), nonreportables' propensity to trade (*PT_Nonrep*) for column (3), and the ratio of noncommercial financial traders' propensity to trade over that of commercial hedgers (*PT_Ratio*) for column (4). The independent variable of interest is the degree of transparency (*Info_Transp*). All variables are defined in the Appendix. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity as well as cross-sectional and temporal dependence are reported in parentheses. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

	(1) $PT\_NonComm_{c,t}$	(2) $PT\_Comm_{c,t}$	(3) $PT\_Nonrep_{c,t}$	(4) $PT\_Ratio_{c,t}$
$\boldsymbol{Info\_Transp_{c,t}}$	**-1.585*** **	**-0.317** **	**-0.531*** **	**-0.344*** **
	(-4.928)	**(-2.382)**	**(-2.836)**	**(-4.034)**
$R_{c,t-1}$	3.836**	0.952	0.680	0.833*
	(2.397)	(1.432)	(0.698)	(1.773)
Commodity FE	Y	Y	Y	Y
Year-week FE	Y	Y	Y	Y
Observations	31,462	31,462	31,462	31,462
Adjusted R-squared	0.239	0.163	0.178	0.106

Table 4: AMIS Setting – Descriptive Statistics

Panel A presents descriptive statistics for the full sample and Panel B displays a comparison of pre-treatment period characteristics between treatment and control commodities. I define all variables in the Appendix. ***, **, and * indicate the significance of the difference between treatment and control commodities at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A: Full Sample

	(1) N	(2) Mean	(3) Std. Dev.	(4) P25	(5) P50	(6) P75
$R_{c,t+1}$ (in %)	5,456	0.208	3.799	-2.108	0.107	2.408
$Hedging\_Pressure_{c,t}$	5,456	0.142	0.196	0.002	0.111	0.247
$Pos\_Chng\_Com_{c,t}$	5,456	-0.001	0.035	-0.019	-0.001	0.017
$PT\_NonComm_{c,t}$	5,456	6.291	4.901	2.786	4.969	8.271
$PT\_Comm_{c,t}$	5,456	4.075	2.944	1.951	3.373	5.344
$PT\_Nonrep_{c,t}$	5,456	6.781	5.361	3.094	5.358	8.614
$PT\_Ratio_{c,t}$	5,456	2.083	1.983	0.932	1.561	2.507
$B_{c,t}$	5,456	0.031	0.215	-0.003	0.032	0.108
$\hat{v}_{c,t}$	5,456	0.295	0.474	0.225	0.420	0.600

Panel B: Pre-Treatment Comparisons

	(1)	(2)	(3)	(4)	(5)
	Treatment Commodities		Control Commodities		Mean Differences
	N	Mean	N	Mean	
$R_{c,t+1}$ (in %)	840	0.452	1,886	0.576	-0.123
$Hedging\_Pressure_{c,t}$	840	0.083	1,886	0.170	-0.087***
$Pos\_Chng\_Com_{c,t}$	840	-0.004	1,886	-0.003	-0.001
$PT\_NonComm_{c,t}$	840	7.393	1,886	6.528	0.865***
$PT\_Comm_{c,t}$	840	4.091	1,886	4.010	0.081
$PT\_Nonrep_{c,t}$	840	6.115	1,886	8.168	-2.053***
$PT\_Ratio_{c,t}$	840	2.290	1,886	2.270	0.020
$B_{c,t}$	840	0.040	1,886	0.100	-0.060***
$\hat{v}_{c,t}$	840	0.437	1,886	0.396	0.042**

Table 5: Change in Cost of Price Insurance around AMIS

Panel A: Main Results

This table examines how the price impact of hedging pressure changes for treatment markets relative to control markets around the AMIS shock. It presents the OLS estimates of Eqn. (4). The dependent variable is commodity futures excess return (*R*) in week *t+1*. The main independent variables are hedging pressure (*Hedging_Pressure*) and commercial hedgers' position changes (*Pos_Chng_Com*) in week *t*. *Treat* is an indicator variable that equals 1 for corn, wheat, KC wheat, Minn wheat, soybeans, rough rice, soybean oil, and soybean meal, and 0 for the other 18 commodities that are unaffected by the AMIS launch. *Post* is an indicator variable that equals 1 for periods after the AMIS launch date (September 2011) and 0 otherwise. I exclude observations within the two years beginning in March 2011. I include data for up to two years before and after the two-year window beginning in March 2011. The *Treat* and *Post* variables are subsumed by fixed effects and thus are not displayed. All variables are defined in the Appendix. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity and well as cross-sectional and temporal dependence are reported in parentheses.

	(1) $R_{c,t+1}$
$\boldsymbol{Hedging\_Pressure_{c,t} \times Treat_c \times Post_t}$	**3.885****
	(2.138)
$Pos\_Chng\_Com_{c,t} \times Treat_c \times Post_t$	-3.442
	(-0.482)
$Hedging\_Pressure_{c,t}$	0.485
	(0.562)
$Pos\_Chng\_Com_{c,t}$	10.734***
	(3.936)
$Treat_c \times Post_t$	-0.309
	(-0.712)
$Hedging\_Pressure_{c,t} \times Treat_c$	-2.329
	(-1.063)
$Pos\_Chng\_Com_{c,t} \times Treat_c$	-0.012
	(-0.002)
$Hedging\_Pressure_{c,t} \times Post_t$	-1.341**
	(-2.299)
$Pos\_Chng\_Com_{c,t} \times Post_t$	-7.280**
	(-2.253)
$B_{c,t}$	-0.027
	(-0.081)
$\hat{v}_{c,t}$	-0.043
	(-0.327)
$R_{c,t}$	2.555
	(1.122)
Commodity FE	Y
Year-week FE	Y
Observations	5,456
Adjusted R-squared	0.248

Panel B: Cross-Sectional Test – Change in Degree of Information Transparency

This table presents evidence of the differential effects of the AMIS launch on price insurance provision for markets that experience differential changes in the degree of information transparency. *HighInfo_Treat* (*LowInfo_Treat*) is an indicator variable for the markets that experience an above-median (below-median) increase in the degree of information transparency (*Info_Transp*) around the AMIS launch. To conserve space, all control variables previously used are included in the regressions but not reported. All variables are defined in the Appendix. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity as well as cross-sectional and temporal dependence are reported in parentheses. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

	(1) $R_{c,t+1}$
$HighInfo\_Treat_c \times Post_t \times Hedging\_Pressure_{c,t}$ [a]	8.334***
	(2.943)
$LowInfo\_Treat_c \times Post_t \times Hedging\_Pressure_{c,t}$ [b]	2.607
	(1.381)
[a] – [b]	5.727**
	(2.165)
Controls	Y
Commodity FE	Y
Year-week FE	Y
Observations	5,456
Adjusted R-squared	0.213

Table 6: Changes in Traders' Propensity to Trade around AMIS

This table estimates the effect of the AMIS launch on traders' propensity to trade. The dependent variable is noncommercial financial traders' propensity to trade (*PT_NonComm*) for column (1), commercial hedgers' propensity to trade (*PT_Comm*) for column (2), nonreportables' propensity to trade (*PT_Nonrep*) for column (3), and the ratio of noncommercial financial traders' propensity to trade over that of commercial hedgers (*PT_Ratio*) for column (4). The *Treat* and *Post* variables are subsumed by fixed effects and thus are not displayed. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity as well as cross-sectional and temporal dependence are reported in parentheses. All variables are defined in the Appendix. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

	(1) $PT\_NonComm_{c,t}$	(2) $PT\_Comm_{c,t}$	(3) $PT\_Nonrep_{c,t}$	(4) $PT\_Ratio_{c,t}$
$\boldsymbol{Treat_c} \times \boldsymbol{Post_t}$	**-1.119*** **	**-0.429** **	**0.145**	**-0.039**
	(-2.781)	**(-2.317)**	**(0.555)**	**(-0.331)**
$R_{c,t-1}$	1.502	0.819	-0.420	-0.345
	(0.573)	(0.582)	(-0.179)	(-0.447)
Commodity FE	Y	Y	Y	Y
Year-week FE	Y	Y	Y	Y
Observations	5,454	5,454	5,454	5,454
Adjusted R-squared	0.168	0.180	0.212	0.054

Table 7: Evidence of the Hirshleifer Effect Channel

Panel A: Change in Risk-Sharing Opportunities for Hedgers around AMIS

This table examines the change in the sensitivity of commercial hedgers' positions to their fundamental hedging demand around the AMIS introduction. The dependent variable is average hedging pressure (*Hedging_Pressure*) for commodity *c* in quarter *q*. The main independent variable is average default risk (*Def_Risk*) for firms with exposure to commodity *c* in quarter *q-1*. The *Treat* and *Post* variables are subsumed by fixed effects and thus are not displayed. All variables are defined in the Appendix. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity as well as cross-sectional and temporal dependence are reported in parentheses. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

	(1) $Hedging\_Pressure_{c,q}$
$Treat_c \times Post_q$	-0.543**
	(-2.347)
$Def\_Risk_{c,q-1}$	0.046***
	(3.351)
$Def\_Risk_{c,q-1} \times Treat_c$	-0.048
	(-0.533)
$Def\_Risk_{c,q-1} \times Post_q$	-0.022**
	(-2.341)
$\boldsymbol{Def\_Risk_{c,q-1} \times Treat_c \times Post_q}$	**-0.168****
	(-2.151)
Commodity FE	Y
Year-week FE	Y
Observations	392
Adjusted R-squared	0.781

Panel B: Change in Risk-Sharing Opportunities for Financial Traders around AMIS

This table examines the change in the responsiveness of noncommercial financial traders' net trading to stock market downturns around the introduction of AMIS. The dependent variable is noncommercial financial traders' net trading (*Pos_Chng_NonComm*) for commodity *c* in week *t+1* to week *t+4*. The main independent variable is an indicator variable that equals 1 if the weekly average S&P 500 index returns fall in the lowest 5th percentile over its history and 0 otherwise (*SP500_5pct*). The *Treat* variable is subsumed by commodity fixed effects and is not displayed. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity as well as cross-sectional and temporal dependence are reported in parentheses. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

	(1) $Pos\_Chng\_NonComm_{[t,t+4]}$
$Post_t$	-0.013**
	(-2.021)
$Treat_c \times Post_t$	0.003
	(0.245)
$SP500\_5pct_t$	0.018**
	(2.588)
$SP500\_5pct_t \times Treat_c$	0.013
	(0.645)
$SP500\_5pct_t \times Post_t$	-0.010
	(-0.769)
$\boldsymbol{SP500\_5pct_t \times Treat_c \times Post_t}$	**-0.075*** **
	(-3.214)
$R_{c,t-1}$	-0.010
	(-0.255)
$R_{c,t-1} \times Treat_c$	0.025
	(0.316)
$R_{c,t-1_t} \times Post_t$	-0.034
	(-0.461)
$R_{c,t-1} \times Treat_c \times Post_t$	0.020
	(0.139)
Commodity FE	Y
Year-week FE	N
Observations	5,320
Adjusted R-squared	0.018

Table 8: Evidence of the Hirshleifer Effect Channel – Cross-Sectional Test

This table presents evidence on how the effect of the AMIS launch on price insurance supply varies by the dispersion of market positions. *Market Position Dispersion* is the market-level average position concentration ratio multiplied by -1. To conserve space, all control variables previously used are included in the regressions but not reported. All variables are defined in the Appendix. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity as well as cross-sectional and temporal dependence are reported in parentheses. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

	(1)
Partitioning variable =	Market Position Dispersion
Dependent variable =	$R_{c,t+1}$
$Treat_c \times Post_t \times Hedging\_Pressure_{c,t}$ $(Above\ median)$ [a]	9.269**
	(1.975)
$Treat_c \times Post_t \times Hedging\_Pressure_{c,t}$ $(Below\ median)$ [b]	1.932
	(1.088)
$Treat_c \times Post_t \times Pos\_Chng\_Com_{c,t}$ $(Above\ median)$ [c]	1.563
	(0.168)
$Treat_c \times Post_t \times Pos\_Chng\_Com_{c,t}$ $(Below\ median)$ [d]	-7.841
	(-0.952)
[a] – [b]	7.337*
	(1.664)
[c] – [d]	9.404
	(0.960)
Controls	Y
Commodity FE	Y
Year-week FE	Y
Observations	5,456
Adjusted R-squared	0.213

Table 9: Evidence of the Information Asymmetry Channel

This table presents evidence on how the effects of the AMIS launch on price insurance provision to commercial hedgers and liquidity provision to noncommercial financial traders vary by the traders' sophistication and disparity in their sophistication levels. *Noncommercial (Commercial) Sophistication* is noncommercial financial traders' (commercial hedgers') average position size. *Disparity in Trader Sophistication* is the signed difference between noncommercial financial traders' average position size and that of commercial hedgers. To conserve space, all control variables previously used are included in the regressions but not reported. All variables are defined in the Appendix. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity as well as cross-sectional and temporal dependence are reported in parentheses. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Partitioning variable =	Noncommercial Sophistication	Commercial Sophistication	Disparity in Trader Sophistication
Dependent variable =	$R_{c,t+1}$	$R_{c,t+1}$	$R_{c,t+1}$
$Treat_c \times Post_t \times Hedging\_Pressure_{c,t}$ $(Above\ median)$ [a]	6.102	2.987	5.181
	(1.221)	(1.189)	(1.503)
$Treat_c \times Post_t \times Hedging\_Pressure_{c,t}$ $(Below\ median)$ [b]	1.178	5.952*	2.768
	(0.546)	(1.702)	(1.096)
$Treat_c \times Post_t \times Pos\_Chng\_Com_{c,t}$ $(Above\ median)$ [c]	-0.548	8.313	-21.39*
	(-0.0516)	(1.458)	(-1.710)
$Treat_c \times Post_t \times Pos\_Chng\_Com_{c,t}$ $(Below\ median)$ [d]	-5.326	-22.465*	7.657
	(-0.652)	(-1.735)	(1.329)
[a] – [b]	4.924	-2.965	2.412
	(0.883)	(-0.844)	(0.703)
[c] – [d]	4.778	30.778**	-29.052**
	(0.402)	(2.560)	(-2.545)
Controls	Y	Y	Y
Commodity FE	Y	Y	Y
Year-week FE	Y	Y	Y
Observations	5,456	5,456	5,456
Adjusted R-squared	0.213	0.212	0.213

Table 10: O&G Disclosure - Change in the Cost of Price Insurance

This table examines how the price impact of hedging pressure changes for treatment markets relative to control markets around the SEC's revision to 10-K oil and gas reserve disclosures. It presents the OLS estimates of Eqn. (4). The dependent variable is commodity futures excess return (*R*) in week *t+1*. The main independent variables are hedging pressure (*Hedging_Pressure*) and commercial hedgers' position changes (*Pos_Chng_Com*) in week *t*. *Treat* is an indicator variable that equals 1 for crude oil, heating oil, gasoline, and natural gas, and 0 for the other 15 commodities that are unaffected by this shock and the AMIS launch. *Post* is an indicator variable that equals 1 for periods after 2009 and 0 otherwise. I exclude observations within the two years beginning in January 2009. I include data for up to two years before and after the two-year window beginning in January 2009. The *Treat* and *Post* variables are subsumed by fixed effects and thus are not displayed. All variables are defined in the Appendix. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity and well as cross-sectional and temporal dependence are reported in parentheses.

	(1) $R_{c,t+1}$
$\boldsymbol{Hedging\_Pressure_{c,t} \times Treat_c \times Post_t}$	**7.920****
	(2.204)
$Pos\_Chng\_Com_{c,t} \times Treat_c \times Post_t$	-17.760
	(-1.548)
$Hedging\_Pressure_{c,t}$	1.029
	(0.930)
$Pos\_Chng\_Com_{c,t}$	-2.912
	(-0.711)
$Treat_c \times Post_t$	-0.488
	(-0.882)
$Hedging\_Pressure_{c,t} \times Treat_c$	-9.396**
	(-2.232)
$Pos\_Chng\_Com_{c,t} \times Treat_c$	14.015
	(1.585)
$Hedging\_Pressure_{c,t} \times Post_t$	-0.447
	(-0.467)
$Pos\_Chng\_Com_{c,t} \times Post_t$	10.691**
	(2.337)
$B_{c,t}$	-0.065
	(-0.193)
$\hat{v}_{c,t}$	-0.273
	(-1.371)
$R_{c,t}$	0.145
	(0.055)
Commodity FE	Y
Year-week FE	Y
Observations	3,862
Adjusted R-squared	0.310

Table 11: O&G Disclosure - Changes in Traders' Propensity to Trade

This table estimates the effect of the SEC's revision to 10-K oil and gas reserve disclosures on traders' propensity to trade. The dependent variable is noncommercial financial traders' propensity to trade (*PT_NonComm*) for column (1), commercial hedgers' propensity to trade (*PT_Comm*) for column (2), nonreportables' propensity to trade (*PT_Nonrep*) for column (3), and the ratio of noncommercial financial traders' propensity to trade over that of commercial hedgers (*PT_Ratio*) for column (4). The *Treat* and *Post* variables are defined as in Table 10. They are subsumed by fixed effects and thus are not displayed. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity as well as cross-sectional and temporal dependence are reported in parentheses. All variables are defined in the Appendix. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

	(1) $PT\_NonComm_{c,t}$	(2) $PT\_Comm_{c,t}$	(3) $PT\_Nonrep_{c,t}$	(4) $PT\_Ratio_{c,t}$
$\boldsymbol{Treat_c \times Post_t}$	**-2.193***** **(-5.127)**	**0.234** **(0.538)**	**-0.846**** **(-2.078)**	**-1.009***** **(-4.387)**
$R_{c,t-1}$	1.187 (0.670)	-0.379 (-0.306)	-0.245 (-0.086)	0.137 (0.139)
Commodity FE	Y	Y	Y	Y
Year-week FE	Y	Y	Y	Y
Observations	3,845	3,845	3,845	3,845
Adjusted R-squared	0.130	0.184	0.175	0.055

Table 12: O&G Disclosure - Change in Risk-Sharing Opportunities for Hedgers

This table examines the change in the sensitivity of commercial hedgers' positions to their fundamental hedging demand around the SEC's revision to 10-K oil and gas reserve disclosures. The dependent variable is average hedging pressure (*Hedging_Pressure*) for commodity *c* in quarter *q*. The main independent variable is average default risk (*Def_Risk*) for firms with exposure to commodity *c* in quarter *q-1*. The *Treat* and *Post* variables are defined as in Table 10. They are subsumed by fixed effects and thus are not displayed. All other variables are defined in the Appendix. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity as well as cross-sectional and temporal dependence are reported in parentheses. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

	(1) $Hedging\_Pressure_{c,q}$
$Treat_c \times Post_q$	-0.497***
	(-5.101)
$Def\_Risk_{c,q-1}$	-0.060
	(-1.694)
$Def\_Risk_{c,q-1} \times Treat_c$	0.263***
	(3.440)
$Def\_Risk_{c,q-1} \times Post_q$	0.050
	(1.787)
$\boldsymbol{Def\_Risk_{c,q-1} \times Treat_c \times Post_q}$	**-0.148*** **
	(-5.561)
Commodity FE	Y
Year-week FE	Y
Observations	194
Adjusted R-squared	0.857

Table 13: O&G Disclosure - Change in Risk-Sharing Opportunities for Financial Traders

This table examines the change in the responsiveness of noncommercial financial traders' net trading to stock market downturns around the SEC's revision to 10-K oil and gas reserve disclosures. The dependent variable is noncommercial financial traders' net trading (*Pos_Chng_NonComm*) for commodity *c* in week *t+1* to week *t+4*. The main independent variable is an indicator variable that equals 1 if the weekly average S&P 500 index returns fall in the lowest 5th percentile over its history and 0 otherwise (*SP500_5pct*). The *Treat* and *Post* variables are defined as in Table 10. The *Treat* variable is subsumed by commodity fixed effects and is not displayed. T-statistics calculated using Driscoll and Kraay (1998) standard error estimates that are robust to heteroscedasticity as well as cross-sectional and temporal dependence are reported in parentheses. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

	(1) $Pos\_Chng\_NonComm_{[t,t+4]}$
$Post_t$	-0.006
	(-0.613)
$Treat_c \times Post_t$	0.007
	(0.887)
$SP500\_5pct_t$	-0.011*
	(-1.738)
$SP500\_5pct_t \times Treat_c$	0.026***
	(2.702)
$SP500\_5pct_t \times Post_t$	0.021
	(1.452)
$\boldsymbol{SP500\_5pct_t \times Treat_c \times Post_t}$	**-0.039****
	(-2.511)
$R_{c,t-1}$	-0.095
	(-1.546)
$R_{c,t-1} \times Treat_c$	0.036
	(0.565)
$R_{c,t-1_t} \times Post_t$	0.072
	(0.804)
$R_{c,t-1} \times Treat_c \times Post_t$	-0.088
	(-0.962)
Commodity FE	Y
Year-week FE	N
Observations	3,625
Adjusted R-squared	0.016

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