Risk and Capital-Labor Allocation: Evidence from Large-Scale Government Insurance Provision*

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Abstract

This study shows that uninsured risk is a driver of within-firm factor input misallocation, even in a context with near-complete factor and credit markets. Using operation-level microdata from the U.S. agricultural sector and regulatory thresholds for identification, we find that increases in insurance use allow operations to increase physical capital investment and reduce total labor use. Our analysis of enterprise value suggests that this reallocation is value-enhancing and is driven by changes in each factor's returns. The decline in total labor use is due to a reduction in supplemental labor; managerial labor increases. Operations fund capital investments using internal savings rather than external capital, implying that reducing cash flow risk, not financial constraints or a declining cost of capital, is the channel through which insurance spurs these changes. Our results identify a significant economic cost of risk and highlight a key benefit of government-sponsored insurance.

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1 Introduction

How does uninsured risk affect firms' production choices? How and why does insurance alter those choices? These questions are central to classic theories of sustainable economic growth and are increasingly relevant due to technological improvements that should spur firms to reallocate factors of production (Autor and Dorn, 2013; Caunedo and Kala, 2021; Mindell et al., 2023).

Uninsured risk is a potential friction in the reallocation process. Theories that relate risk management to firm decisions posit that risk not only drives differences between the marginal costs of capital and labor within a firm, (Fazzari and Petersen, 1993; Pindyck, 1993; Dixit, 1997), but also between different types of labor (Bhandari and McGrattan, 2021). Recent empirical evidence shows that uninsured risk leads to resource misallocation in terms of capital and labor (Bloom et al., 2007; Asker et al., 2014; Karlan et al., 2014).

Our paper provides new empirical evidence about risk management: that it allows firms to change *how* they allocate investment across factor types. In the absence of risk management, firms may allocate labor and capital in order to mitigate uninsured risk. That allocation may differ from the firm's optimal, profit- or productivity-maximizing allocation. Analyzing a natural experiment that changed access to risk management tools over time, we show that an increase in crop insurance allowed U.S. agricultural operations to reallocate capital and labor, which ultimately increased their value.

We exploit variation in an agricultural operation's ability to increase crop insurance use following a series of national changes in incentives to adopt more insurance between 2000 and 2014. Crop insurance is the primary component of the federal government's farm safety net; take-up for many crops became nearly universal during our study period (Rosch, 2021). We construct an instrumental variable based on an explicit limit on the percent of revenues that can be covered by insurance. This maximum ceiling on an operation's insurance use is externally determined at the federal level. We instrument for an operation's change in insurance use with the distance between its initial insurance use and that ceiling: incentives

to buy more insurance increased over time but operations with coverage near the ceiling could not increase insurance use as much as those with coverage farther from it (Weber et al., 2016).

To study how larger versus smaller increases in insurance use affected operations' behavior, we use operation-level panel data from the restricted-use United States Department of Agriculture (USDA) Agricultural Resource and Management Survey (ARMS). ARMS surveys a random sample of operations annually, creating an unbalanced panel of firm-level data. These detailed microdata include operations' labor use, capital investment, debt financing, current spending, and enterprise value. The main treatment variable is the change in firm-level crop insurance use over time.

Our empirical strategy compares changes in investment decisions by operations with large increases in insurance use to those with small increases in insurance use. Our primary empirical model estimates the changes in within-operation factor allocations caused by changes in crop insurance using a two-stage least squares (2SLS) model with operation-level first differences. The IV is systematically related to an operation's ability to increase crop insurance use, and the first differences absorb time invariant characteristics of the operator or operation that may jointly determine insurance use and our outcomes. The key identifying assumption is that the IV, the initial distance to the insurance limit, affects investment decisions only through its impact on the operation's between-year insurance change.

Our results show that for every 1% increase in insurance use, the average operation reduces total labor hours by 5% and increases investment in machinery by 1%. There are economic gains from mechanization and the evidence in our paper is consistent with insurance-induced capital-labor substitution triggering improved firm value (Caunedo and Kala, 2021). Specifically, we find that total enterprise value increases.[1] Mechanization is the key to development and growth in the agricultural sector (Binswanger, 1986). Our paper

[1]Crop insurance premiums are subsidized by the federal government. In section 5.2.2, we estimate an upper bound for the subsidy transfer during our study period and show that it is a small fraction of the increase in enterprise value. For more information on the federal crop insurance program, see section 2.

shows the role of risk management in alleviating barriers to this ongoing process of economic transformation.

These firm-level changes are unlikely to be driven by coordinated insurance-investment decisions, mean reversion in production opportunities, or lender policies that favor insurance.[2] Moreover, operators have strong incentives against moral hazard or risk-shifting behaviors (Rayo, 2007). The federal crop insurance program includes features designed to mitigate moral hazard, and most row crop operations are privately-held, sole-proprietorships, and many are inter-generational, family businesses (Whitt et al., 2019).[3]

The biggest threat to identification is the potential correlation of the initial insurance choice with changes in firm decisions or with time-varying firm or operator characteristics. Our IV uses an operation's initial insurance use choice as a share of the exogenous initial maximum. This can be compared to a pretreatment exposure share in a Bartik or shift-share IV, which provides a useful parallel for understanding how our IV is both relevant and does not violate the exclusion restriction.[4] In addition, we refer to standard industry practices to rule out confounding factors, such as the fact that operators tend to choose insurance to cover per-acre expenses and the maximum is not a salient statistic as they make the insurance decision.[5]

[2]Crop insurance use and investment may be linked through lender preferences, although empirical evidence and industry norms suggest a relationship only between insurance and short-term operating loans, but not long-term loans or leverage (Ifft et al., 2015, 2024).

[3]The revenue that is covered by crop insurance is based on an operation's past performance (Mieno et al., 2018). Further, the USDA performs loss adjustment inspections and uses data mining techniques to detect fraud (Little et al., 2007; Office of the Inspector General, 2017). These features jointly increase incentives to report honestly and maximize firm value.

[4]SSIVs have two components: "exposure shares" and "shocks". The share is often a lagged measure of exposure, for example, lagged share of Cuban immigrants or lagged employment shares. There could be single shock (i.e., Mariel boatlift) or multiple shocks (i.e., exports by industry), which are universal and (often) exogenous. Our IV essentially is a unique operation-level exposure share, which we refer to as the coverage ratio and establish to be relevant or have strong predictive power for an operation's increase in insurance use. Likewise, there is a common shock: exogenous increases in government support for crop insurance. We argue that conditional on our first differences empirical model with controls for the initial exposure share, violations of the exclusion restrictions would involve an unrealistic and stylized investment-insurance cycle. Balance tests and the staggered survey sampling methodology reinforce this argument.

[5]Insurance decisions must be made before planting begins each year. Because the operation-specific total cost of the maximum possible insurance takes into account planted acres, our maximum insurance measure is not determined until planting is complete. Hence, it is only fully known ex-post.

To investigate why risk management causes a reduction in labor and an increase in capital, we to explore whether these results are driven by changes in the marginal productivity or the price of these factor inputs. We use granular data on labor use to disaggregate the result on total labor into worker types and find that the reduction in total labor use comes entirely from supplemental labor. Managers (i.e., primary operators) actually increase their labor hours. Theoretically, managers may be more efficient in production, due to increased expertise and reduced agency costs whereas supplemental labor may be easily replaced by machinery (Tufano, 1998; Bhandari and McGrattan, 2021).[6] Risk management triggers operations to shift towards more specialized labor.

Further exploration of the increase in investment in physical capital suggests that this is not due to declining costs of financial capital but instead due to complementary shifts away from labor-intensive machinery. We observe no increase in operations' use of equipment-specific debt. Instead, we observe operations increasing current spending on machinery and using more machines that are less labor intensive.[7] Our analysis provides evidence that operations use the reduction in risk to transform precautionary savings into labor-saving capital. These results are consistent with a concurrent trend in the agricultural sector in which crop insurance use has increased while liquid asset holdings have declined (Zulauf and Schnitkey, 2024).

The primary contribution of our paper is to document the direct and causal role of risk management in firms' factor allocation decisions. We focus on how firms shift investment between specific factors of production, rather than on how firms change total investment. Our results provide empirical support for recent theoretical models predicting how risk management affects capital misallocation and improves labor and production efficiency within

[6]Using the sub-sample of operations that report having other sources of income, we see suggestive evidence that at least one type of supplemental worker reallocates their labor to off-farm work, indicating a potential increase in the opportunity cost of their time or a comparative disadvantage in terms of on-farm productivity.

[7]In a sub-sample analysis, we examine machinery characteristics and show that the machines used on operations in this subsample are less labor intensive than the operation's other fixed capital but do not differ in terms of other observable characteristics, such as age, size, and horsepower.

firms (Ai et al., 2019; Bhandari and McGrattan, 2021; Bhandari et al., 2021; Donovan, 2021). We find that the overall reduction in labor use is driven by a substitution from non-operator labor to operator labor. In combination with our results on types of capital investment, these findings suggest that labor-saving capital is a substitute for some types of labor and a complement for others. This is important given that recent technological developments are altering the relative value of machines, intangible technology, and human capital (Acemoglu and Restrepo, 2018).

Our paper is most closely related to the model proposed by Karlan et al. (2014). This paper explores the interplay between risk management and factor input allocation and documents how operators respond to risk management tools by increasing investment in yield-linked inputs. Cole et al. (2017) and Emerick et al. (2016) also examine how the introduction of risk management tools changes firms' production decisions. These papers examine a developing country context, and the tool in question is often unfamiliar and newly introduced into these settings as part of the experimental research design. In these settings, therefore, take-up is a crucial concern. This is not the case with crop insurance in the U.S. First, crop insurance is not novel: the first crop insurance products were introduced in 1938 (Rosch, 2021). In addition, it is an extensive, federally administered program, and by the end of our study period, almost 300 million acres were covered by crop insurance policies. Finally, our panel dataset covers agricultural operations over many years, which allows us to examine long-term production decisions.[8] Our results show that even in contexts with highly functioning, well-established factor, insurance, and financial markets, tools to manage risk are a central determinant of how agricultural operations manage factor allocation.

Thus, a second key contribution of our paper is to establish that insurance markets have a first-order effect on a firm's factor allocation that is independent of capital markets.

[8]The agricultural economics literature has examined the effects of federal crop insurance on variable inputs, like chemicals, (e.g. Chang and Mishra, 2012; Ifft and Jodlowski, 2024) and crop choice (e.g. Walters et al., 2012; Claassen et al., 2017). Using a similar identification strategy to ours, Weber et al. (2016) finds no relationship between crop insurance and any kind of chemical input expenditure. Our contribution is to examine crop insurance's effect on longer-term investment in agricultural production's fundamental inputs.

Economic theory suggests that increased investment could happen through a loosening of an operation's credit constraints or, more directly, by allowing an operation to smooth income over time (Stulz, 1996; Karlan et al., 2014). Campello et al. (2011) and Cornaggia (2013) document that risk management opens credit markets which, in turn, increases a firm's capital investment and may also improve firm productivity. Empirical studies establish that risk management operates through capital markets to increase overall investment (Butler and Cornaggia, 2011; Karlan et al., 2011; Bergman et al., 2020; Thakor, 2022). Giroud and Mueller (2015) show that firms reallocate capital and labor across competing projects when they face financial constraints. While these works have established that credit markets are the mechanism that drives the relationship between risk management and total investment, we show that in our context, financial constraints are not limiting capital investment. Instead, we find that these changes occur independently of credit markets and that risk management *directly* changes a firm's production decisions without mediation from credit markets and in the absence of credit constraints.

Finally, our results uncover an additional and incidental benefit of government policy designed to reduce uncertainty. We find that government insurance provision directly changes investment and labor allocation decisions. Even when production is highly mechanized and financial markets are readily accessible, risk management is instrumental in promoting technology adoption and labor reallocation within a firm.

2 Background

The U.S. agricultural sector provides an ideal empirical setting to evaluate these dynamics. Research on other industries must contend with significant heterogeneity across firms in terms of their insurable risks, optimal production processes, and accessibility of output markets. Commodity crop operations produce a homogeneous output using a production process with little variation across operations. Another unique feature of agriculture and other land-based

industries is the near impossibility of firm relocation. In other industries, firms often retain the option of off-shoring to maintain current production levels. Thus, it is challenging to observe firms' direct substitution behavior between primary factors like capital and labor.

The vast majority of row crop operations are family-owned. Labor is typically supplied by one primary operator and several other workers, who are often part of the primary operator's immediate family, including his spouse. The primary operator is the manager, having the most responsibility for both long-term strategy and day-to-day decision making. The other workers provide supplemental labor, which tends to be seasonal, part-time, or both. The labor of primary operators is in high demand year-round, while demand for supplemental labor peaks when weather and seasonal shifts create pressure to complete planting and harvesting quickly. The typical row crop operation is highly mechanized and the requisite physical capital is costly. Therefore, machinery and land both necessitate long-term investments. Planting and cultivation require large tractors and other specialized equipment for particular tasks; these have been getting larger over time. Improvements in machinery through characteristics such as size or speed have allowed operations to substitute machinery for agricultural labor (Wang et al., 2018).[9]

Risk management is valuable to agricultural operations because both crop yields and prices are subject to substantial volatility. Crop insurance is the primary tool to manage this risk. Following policy changes made in 1980 through the late 1990s, the federal crop insurance program became the foundation of the current federal farm safety net (Bulut et al., 2012; Glauber, 2013).[10]

Despite the ubiquity and scale of the federal crop insurance program, there is little

[9]Corn planters could cover 4-6 rows in the 1950s and can now cover up to 36 rows. `https://www.farmprogress.com/farming-equipment/world-s-largest-planter-john-deere-s-db120` Other examples include: a single operator using a "high speed planter" to drive faster while planting. Likewise, "seed tenders" partially automate the filling of planters with seed. During harvest, operators can continue harvesting while simultaneously offloading the crop using a "grain cart" rather than stopping to fill a "wagon" with the crop.

[10]The use of private hedging tools, such as futures and options, is low relative to the use of crop insurance and marketing contracts. Other common risk management strategies include on-farm storage and diversification (Prager et al., 2020).

causal evidence about its effects on operations' investment decisions. Much of our knowledge of crop insurance and investment comes from field experiments or contexts that study its introduction, where take-up is a concern and higher labor use tends to be the optimal production response (e.g. Cai et al., 2015; Emerick et al., 2016; Casaburi and Willis, 2018). This is not the case with U.S. crop insurance: coverage for commodity crop operations, the target recipients of the program, is almost universal (Rosch, 2021), and mechanization is largely value-maximizing. Figure 1 shows the intensity of program usage across the country.

[FIGURE 1 ABOUT HERE]

The crop insurance program is entirely centrally managed by a national agency. Insurance products and pricing decisions are determined by the Risk Management Agency (RMA) of the USDA. Any meaningful changes in insurance availability therefore occur outside of the control of local insurance agents or customers.[11] The most widely used federal crop insurance products are policies that insure revenue risk at the operation-crop level.[12] Every year, prior to planting, operators select a coverage level: a percentage of their revenues that they would like to insure. Higher coverage levels have higher premiums, within a given year, crop, and county.[13] With this choice, most operators aim to balance cost-effectiveness with adequate coverage of per-acre production costs, and they choose plans that integrate well with the

[11] Although operators purchase insurance from local crop insurance agents, these agents are employed by private companies, not the government, and therefore cannot influence the premium rates (i.e., offer a discount) and must use those that are set by the RMA. These agents are still valuable to operators because of their local knowledge. They provide information about policy premiums, options, and risk scenarios, which helps each individual operator select his optimal coverage. The companies that employ these agents receive a subsidy based on the policies sold and also share in underwriting risk (losses and gains).

[12] These policies are single-crop plans that cover multiple perils. For producers of commodity crops, yield-only policies are available, but are dominated by revenue policies.

[13] Coverage levels typically range from 50-85% of the operation's guaranteed revenue in 5 percentage point increments. Guaranteed revenues are calculated as an operation's historic yields multiplied by pre-planting futures prices for the insured crop (Rosa, 2018). Historic yields, referred to as actual production history (APH), equal the operation's average yield over the last five to ten seasons. Harvest (fall) futures prices in February are the relevant prices for most spring-planted crops. Most revenue policies select the 'harvest price option', which effectively resets the guarantee with harvest prices, if harvest prices are higher than the pre-planting price. Indemnities are triggered when actual revenue drops below the selected coverage level (percent) of guaranteed revenue. Crop insurance therefore uses the value of the crop itself as the underlying asset to set the crop insurance revenue guarantee. It is not linked to the value of other assets used for production, like machinery.

other business management strategies and objectives of the operation.[14] The premiums are required by law to be actuarially fair and are subsidized by the federal government. Operators pay premiums in a lump sum, minus the subsidy, at the end of the harvest season.[15]

In this paper, we leverage a change in the program to form our identification strategy: during our study period, the subsidized portion of crop insurance premiums increased, making it cheaper for operators to select higher coverage (Rosch, 2021).[16] Research has shown that operators' coverage levels have moved closer to the 'optimal insurance' implied by expected utility over time (Du et al., 2017). This movement is likely a combination of learning and these policy changes designed to increase uptake.

3 Data and empirical strategy

3.1 Data and summary statistics

We use firm-level, restricted-use data from the USDA ARMS. ARMS uses a complex stratified sampling procedure that draws a random sample of approximately 20,000 agricultural operations annually, collecting information on an operation's management practices, income statement and balance sheet, and the operator's demographics. ARMS includes detailed, operation-level information about insurance use, labor allocation, capital investment expenses and value, and financing choices.

[14]Other factors that may contribute to the choice of coverage level include production conditions, perceived risks, and the price-per-acre cost of insurance. It is also based on factors such as their crop yield and price risk, financial solvency, and risk tolerance (Plastina and Drollette, 2021). Conventional wisdom states that the typical operator aims to insure the level of per-acre expected revenues that cover per-acre production expenses. Neither policy nor management norms incentivize considerations of coverage levels beyond the current year. Operations are not financially constrained from adopting higher crop insurance coverage because premiums are not due until harvest when revenues are realized. Further, crop insurance premiums are a small share of variable expenses. For operations specialized in corn production in 2014, *all* insurance premiums, including crop insurance, were about 5% of cash expenses. See: `https://my.data.ers.usda.gov/arms/tailored-reports`.

[15]Premium subsidies decline as a percent of total cost as coverage rates increase; these subsidies reduce the up-front cost of insurance and are not a direct cash transfer. We discuss the potential wealth effects of the subsidy during our study period in more detail in Section 5.2.2.

[16]For example, an operator that chose 70% coverage initially would be spending relatively less for the 70% coverage later in the sample.

As a result of intentional oversampling of large operations, ARMS observations can be linked across multiple years, creating an unbalanced panel of operations that are sampled in more than one year (Weber et al., 2016).[17] For our analysis, we restrict the sample of repeat operations to those that have participated in crop insurance in at least two years and have a minimum of $10,000 in the value of production of commodity row crops for which widespread crop insurance is readily available.[18] These data restrictions reduce the likelihood that we compare operations for which crop insurance is relevant to those for which it is not. There are 13,169 unique operations in the years between 2000 and 2014 that fit these criteria. We do not observe operations in every year; most operations appear only twice (90%), although some appear between three and seven times. An operation can first appear in the sample in any year between 2000 and 2013. Moreover, because the subsequent year(s) of observation are also random for each operation, the period between observations can be as short as one or as long as 13 years. Our final sample is an unbalanced panel of 27,790 operation-year observations. Our primary model uses first differences; when these observations are differenced, there are 14,621 operation-pair-of-year observations.[19]

Table 1 reports operation- and operator-level characteristics for this sample. Insurance use is recorded along two margins: the dollar value of crop insurance premiums paid per acre operated and the number of acres insured. The average operation in our sample pays a premium of $7.22 per acre and enrolls about 65% of acres operated in crop insurance.[20] Premium values are our preferred measure of insurance, as they reflect the operator's chosen coverage level (i.e., percent of revenue insured). Holding constant the crop being insured, operators pay higher insurance premiums per acre for higher coverage levels. Primary oper-

[17] Weber et al. (2016) describes differences between repeat operations and those that appear only once.

[18] These crops are: barley, canola, corn (for grain or silage), cotton, oats, sorghum, soybeans, and wheat. These crops together made up about 80% of all federal crop insurance program liabilities (RMA, 2014).

[19] Appendix B describes the process used to create our panel dataset in detail, including the number of observations dropped as a result of imposing each of these sample restrictions. Table B3 reports the number of operations in our final sample disaggregated by the number of times they appear in our sample.

[20] Acres operated is a broad category that includes land not used for growing crops, such as grazing land. Other work on crop insurance participation has shown that enrollment rates of land planted with crop-insurance eligible crops approaches 100%, especially in the later years of our sample (Rosa, 2018).

ators are male (98%), married (89%), and white (96%), on average. We also observe how the operation allocates acres across the three primary commodity row crops and the operation's primary output or specialization. The majority of operations specialize in row crop production.[21] The operations farm around 2,200 acres with total annual cash operating expenses of more than $1 million; most operations have revenues of $500,000 or more. All dollar values are reported in 2013 CPI-adjusted dollars.

[TABLE 1 ABOUT HERE]

Table 2 reports summary statistics for variables related to an operation's labor, capital investment, and financing decisions. For each operation, ARMS reports the labor hours used in agricultural production by worker type: primary operator and supplemental labor. The primary operator supplies the most labor per year to the operation: almost 54 hours per week, on average. [22]

[TABLE 2 ABOUT HERE]

The ARMS survey reports physical capital investment measured as the estimated market value of farm machinery. Farm machinery typically belongs to one of three broad categories: tractors, self-propelled machines, and non-self-propelled machines.[23] We construct a ratio of capital and labor substitution used in agricultural production for each operation, measured as the dollar value of machinery divided by total agricultural labor hours. The survey also reports the market value of cars and trucks owned by the operation and the value of its real estate, which is the most valuable asset held by an operation at more than $2.5 million on

[21]Specialization indicates where the operation derives the majority of its value of production, and does not preclude operations from producing multiple crops as part of their operation. The preponderance of row crop operations in our sample reflects our sample restrictions.

[22]Wages are not reported systematically in ARMS; in general, agricultural wage data tend to be noisy, with high variance year-to-year or are not reported due to the high preponderance of family labor. Labor variables reported in hours are winsorized at the 99% level to remove outliers. All other variables that we use have been cleaned (verified statistically and adjusted to survey weights by NASS (National Agricultural Statistics Service)). NASS does not make these adjustments to variables measured in hours.

[23]See Appendix B for the definitions and examples of these categories.

average. Respondents also record the operation's enterprise value, which is the combined value of the operation and household net worth.

3.2 Estimation: IV model

Estimating the causal effect of insurance on labor and capital allocation requires variation in the use of insurance that is unrelated to the decision to reallocate factors of production. In our setting, operations use crop insurance to manage risk. Ideally, we would have an experimental setting in which crop insurance is assigned randomly to some operations and not to others, thereby reducing concerns about (1) spurious correlations between crop insurance, investment, and management decisions and (2) unobserved operation characteristics such as investment opportunities and risk preferences that might be correlated with insurance and other production choices. We construct an IV, developed by Weber et al. (2016), to address these concerns and recover the causal relationship between risk management and factor input allocation. This IV can be understood in the context of shift-share IVs as it has the following components: (1) an operation-level pre-treatment exposure share with both an exogenous and potentially endogenous component and (2) common exogenous incentives, or shifts, that universally increase demand for crop insurance.

There are inflexible features of the federal crop insurance program that underlie these components of the IV. The maximum coverage level, called a coverage limit, is set by the government, typically at 85% of expected revenue. This strict limit defines the exposure share: the closer an operation's coverage level is to that coverage limit, the less they are able to increase their coverage level in later years. The instrument binds because of entirely exogenous shifts: policy incentives to adopt higher coverage levels increased over our sample period. Operations with higher initial coverage levels (i.e., closer to the coverage limit) were unable to respond to those incentives the same way that operations with lower initial coverage levels were. Specifically, the cost of the same coverage level declined over time as the portion of the premium subsidized by the government increased. At the same time, market

forces such as higher crop and input prices and greater price volatility made higher coverage more attractive. Therefore, the relationship between an operation's initial proximity to the coverage limit and its ability to increase insurance use is negative. Further, because an operation's possible increase in insurance use increases (decreases) exponentially the further (closer) its initial insurance use is from the maximum, the relationship is negative *and* non-linear. Figure 2 provides an intuitive illustration of how the instrument functions.

[FIGURE 2 ABOUT HERE]

This negative, non-linear relationship between the between-year change in insurance use and the proximity of initial insurance use to maximum use can be described with an exponential function of the form: $(\frac{P_{i,t}}{P_{i,s}}) = (\frac{P_{i,s}}{\text{Max}P_{i,s}})^{\Theta}$, where $P_{i,s}$ and $P_{i,t}$ are operation i's insurance use (i.e., premium paid per acre) in initial year s and later year t, respectively; $\text{Max}P_{i,s}$ is the operation's maximum possible insurance use in year s. Θ is presumably negative due to the growing incentives to increase insurance use over the sample period. Taking the log of both sides gives:

$$\ln(P_{i,t}) - \ln(P_{i,s}) = \Theta \ln\left(\frac{P_{i,s}}{\text{Max}P_{i,s}}\right) \tag{1}$$

The left-hand side denotes the change in insurance use: the difference in the log of operation i's insurance use between years t and s. On the right-hand side is the IV for this difference, which we refer to as the coverage ratio. The coverage ratio is an operation's initial insurance use divided by the operation's maximum possible insurance use in year s. As the coverage ratio gets larger, the operation's insurance use is closer to the binding constraint and thus $\ln(P_{i,t}) - \ln(P_{i,s})$ must be smaller. As such, the coverage ratio acts as an exposure share and measures an operation's ability to increase insurance use between years.

To calculate an operation's maximum possible insurance use ($\text{Max}P_{i,s}$), we start with the number of acres operation i planted with an insurable commodity in year s. Then, we use the USDA RMA's Summary of Business Data, which records every available crop insurance

policy for any given crop, county, and year. For each county-year-crop triad, we extract the policy with the highest premium per acre, corresponding to the highest coverage level. We then match these plans to each operation in our sample and multiply the per-acre crop-specific premium by the number of acres the operation planted with that crop. We then sum the crop-specific premiums and divide by acres operated to get the maximum possible premium per acre the operation could have paid in that year. Thus, the maximum insurance use is unique to an operation and varies due to differences in county, crop mix, and year.

Measuring insurance use as a difference between any two years s and t lends itself to using a model with first differences, rather than operation fixed effects. As such, an observation in our sample represents an operation i in a pair of years s and t, with $t > s$. Because we observe the majority of our sample only two times, we observe only one change in insurance use for most operations. There are a total of 14,621 unique first-differenced observations.

Our baseline IV model, which we estimate with 2SLS, can be described by the following two-equation system:

$$\Delta\ln(\text{Insurance})_{i,t-s} = \delta_0 + \delta_1 \text{Coverage ratio}_{i,s} + \delta_2 P_{i,s} + \delta_3 \boldsymbol{\Delta G_{i,t-s}} + \tau_{i,s} + \tau_{i,t} + v_{c(i)} + \varepsilon_{i,t-s} \tag{2}$$

$$\Delta\ln(\text{Outcomes})_{i,t-s} = \beta_0 + \beta_1 \Delta ln(\widehat{Insurance})_{i,t-s} + \beta_2 P_{i,s} + \beta_3 \boldsymbol{\Delta G_{i,t-s}} + \tau_{i,s} + \tau_{i,t} + v_{c(i)} + \vartheta_{i,t-s}. \tag{3}$$

In the second stage, given by equation (3), we use the instrumented insurance use, $\Delta ln(\widehat{Insurance})_{i,t-s}$, to measure the impact of a change in insurance use from year s to year t on a change in an operation's labor and capital, enterprise value, and financing and spending decisions.[24] $\boldsymbol{G_{i,t-s}}$ are first-differenced operation-level characteristics: operator age

[24]We also examine the effect of a change in insurance use on the change in the log of the capital-labor ratio from year s to year t. Bartlett and Partnoy (2020) show that using the log-transformation of the ratio as an outcome variable in regression estimation imposes the assumption that the elasticity of the numerator with respect to the denominator is exactly 1. If this elasticity is not 1 and a covariate is correlated with the denominator, the coefficient estimates may be biased, potentially severely. In our model, this restriction is problematic because we are estimating the effect of insurance use on changes the substitution between

and age squared to control for life cycle dynamics, operation size measured in acres operated, and the share of acres planted for the three main insurable commodities to control for insurable crop specialization. The year-of-observation fixed effects $\tau_{i,s}, \tau_{i,t}$ control for year-specific conditions, such as extreme weather, trade wars, federal subsidy rates, and nationwide commodity price movements that may have affected the agricultural sector overall. The year effect is an important control given the general increase in commodity prices across our study period. County fixed effects $v_{c(i)}$ address any local time-invariant characteristics related to agricultural production, such as soil type and land quality. In addition, given that the IV, $\ln\left(\frac{P_{i,s}}{\text{Max}P_{i,s}}\right)$, is not perfectly predicted by initial insurance use, we include a control for $P_{i,s}$, the level of initial insurance use. Doing so addresses concerns about the potential correlation between an operation's initial insurance use and changes in the outcomes studied. Our results are unaffected by this control variable.

In the first stage, given by equation (2), we use the coverage ratio as an instrument for an operation's between-year change in insurance use. The results from the first stage regression, reported in table 3, reveal a strong correlation between the coverage ratio and changes in insurance use. Specifically, a 1% increase in the natural log of the coverage ratio is associated with a 0.3% reduction in the between year change in insurance use. The F-statistic of 116.89 is well above the cutoff for a strong IV (Bound et al., 1995; Stock et al., 2002).

[TABLE 3 ABOUT HERE]

capital and labor directly. When the model uses a logarithmic transformation of this ratio as the outcome variable, we include the log of the denominator as a right hand side control variable to relax the assumption that the elasticity of capital with respect to labor is exactly one. In this case, the second stage regression specification is:

$$\Delta\ln\left(\frac{K}{L}\right)_{i,t-s} = \beta_0 + \beta_1 \Delta ln(\widehat{Insurance})_{i,t-s} + \beta_2 P_{i,s} + \beta_3 \boldsymbol{\Delta G_{i,t-s}} + \beta_4 \ln\left(\frac{L_s}{L_t}\right) + \tau_{i,s} + \tau_{i,t} + v_{c(i)} + \vartheta_{i,t-s}$$

In this case, one plus the β_4 equals the elasticity of substitution between capital and labor.

3.3 Identification: IV Exclusion restriction

The validity of this instrument rests on satisfying the exclusion restriction that the coverage ratio affects an operation's labor use and physical capital investment only through its impact on changes in insurance use. Our instrument is based on 1) explicit insurance coverage limits codified in the federal crop insurance program regulations and 2) changes in exogenous national policies that incentivized operations to increase insurance use towards that limit. It is straightforward to establish that both these limits and policies are exogenous to individual operators' decisions about their crop insurance usage. Remaining concerns relate to the possibility that an operation's initial coverage ratio would either directly influence *changes* in our outcome variables or that the coverage ratio affects changes in our outcome variables through channels other than the change in insurance use.

The federal government stipulates most features of the crop insurance program. These include the increasing incentives for take-up over time, in the form of higher premium subsidy rates, as well as constraints on participation, in the form of explicit insurance coverage limits. Thus, the denominator of the coverage ratio, $\ln(\text{Max}P_{i,s})$, is beyond the control of both operators and their insurance agents and is assigned based on an operation's county and year. Because operations are randomly sampled, initial year s differs for each operation and so the sampling procedure essentially randomizes the maximum insurance use in year s across operation-year observations.

Our first-differences specification absorbs time invariant operator and operation characteristics, and it includes controls for changes in the operator's age, the operation's size, and the operation's crop mix. Furthermore, we include the operation's initial insurance use in levels to control for the possibility that this value is related to our outcomes. By including both $\ln(P_{i,s})$ and $P_{i,s}$ in our model, violations of the exclusion restriction would need to arise beyond the linear relationship between the difference in logs of the outcomes, the level of initial insurance use, and the log of the initial insurance use in the IV.

We show that operators make their choice of initial coverage in a way that is not correlated

with initial levels of our outcome variables. We regress an operation's initial observed level of insurance use $P_{i,s}$ on initial levels of the outcome variables and time varying characteristics in table A1. We also include county-by-year fixed effects, such that operations are compared only to other operations in the same county and year, who would have faced the same insurance choice set. We find no systematic relationship between the initial insurance use and initial levels of any of our outcome variables. In addition, we examine the differences in means for these outcomes' initial values by coverage level terciles. The results, reported in table A2, suggest strong covariate balance in the initial values of investment and labor use across the distribution of coverage ratios.[25]

As in more canonical shift-share IV settings, the primary concern is that initial share predicts changes in the outcomes either directly or indirectly, through mechanisms other than the change in insurance use. In our setting, the former reflects a misconception about how insurance and investment decisions are made. In this hypothetical situation, there would need to be investment cycles, such that conditions that promote machinery investment also promote crop insurance use. Thus, when a good investment opportunity arises, the operator selects high insurance use.[26] The observed change in investment would thus be zero, reflecting that the operator already invested "to capacity" rather than limits on insurance use curtailing investment. The change in insurance would also be zero because the operator did not need to invest. This scenario, and others like it, is inconsistent with the way that crop insurance functions, the nature of agricultural investments, and the policy environment during our study period. This anticipatory insurance "gaming" assumes a model where a single investment occurs over the life-cycle of an operation.[27] Instead, the multiple types of

[25]In table A2, we compare operations across the terciles of the coverage ratio by calculating the differences in means of each outcome in the initial year. The first, second, and third tercile of the coverage ratio is 0.05, 0.28, and 0.86, respectively. To evaluate their statistical significance, we calculate their normalized differences, which should be less than 0.25 so as not to interfere with linear regression analysis (Imbens and Wooldridge, 2009). Most normalized differences we observe are less than 0.10 and the largest normalized difference is 0.15, well below the 0.25 cutoff.

[26]This hypothetical situation is akin to a mortgage company requiring that a home buyer obtain homeowners' insurance. However, crop insurance and investment are not linked in this way: nonetheless, we provide the following discussion to illustrate the differences.

[27]It is also important to note that the insurance decision is very difficult to "dynamically game" or even

machinery used on these operations require continuous investment; there is no target level of investment after which operations no longer upgrade, update, or replace their machinery. Further, conditions that are attractive for investment typically arise at the geographic and sector level due to the homogeneity of the output, not at the operation level.

Finally, our empirical context and the nature of our data make it even more unlikely that factors other than changes in insurance use, such as coordinated investment-insurance decisions, autocorrelation, or mean reversion in investment cycles, drive our results. Both the initial and subsequent year(s) of observation are random for each operation, creating a staggered panel of operation-year observations. The interval between the initial and subsequent years can be as short as one or as long as 13 years and we initially observe operations in a randomly sampled year between 2000 and 2013. One operation's initial year may be another operation's subsequent year and vice versa. In order to violate the exclusion restriction, these hypothetical factors would need to arise from time-variant unobservable confounders that are correlated not only with the initial year of observation, but also with (1) the randomly sampled subsequent year of observation, and (2) the random time interval that lapsed between these dates.[28] Hence, the survey sampling procedure randomizes the conditions under which operations make insurance use and investment decisions over time. Further, because our outcome variables are measured in changes, these dynamics introduce random noise in the cross-section and time-series that is orthogonal to both changes in insurance and investment as well as their initial values. Strategic or anticipatory behavior, like the kind described above, would need to be consistent over these random intervals.

plan for multiple years, because prices are set centrally and are outside the control of both buyers and sellers of crop insurance. Even the cost of an individual crop insurance policy is unknown for the following year, let alone the extent to which future years' insurance subsidy premiums will differ. Further, crop insurance costs are a small share of per-acre expenses and are only paid around harvest time; financial constraints are less relevant to the insurance decision. Operators thus have strong incentives to make their decision for only the current production year.

[28]For example, the data sampling procedure may survey two operations in initial year s that are similar in terms of their insurance use and choice of capital investment. However, the operations are unlikely to have the same subsequent sampling year t such that one may be surveyed two years later and the other might be surveyed 10 years later. Suppose that these operations both chose high insurance use and high capital investment in initial year s: it is unlikely that the operation sampled 10 years later refrained from investing over this interval due to its initial level of investment.

4 Results

This section presents our main findings of the effects of insurance use on a firm's investment in factor inputs (section 4.1) and the changes in each factor's returns that may underlie this reallocation (section 4.2).

4.1 Main results: Does risk management lead to factor reallocation?

When firms face uncertainty, they may need to adjust production parameters more frequently. This changes the marginal costs of factors of production, as adjustment costs tend to be lower for inputs that are easier to reverse (Pindyck, 1993; Dixit, 1997). These costs can distort a firm's investment allocation because the allocation that optimally mitigates risk is not necessarily the one that maximizes efficiency. Risk management tools, like insurance, should reduce these distortions. In our context, specialized agricultural machinery is irreversible compared to labor, which can be used more flexibly. Following this framework, higher insurance use should lead to higher machinery investment and lower labor investment.

Our main results, reported in table 4, support this prediction. Using our IV to test for a causal relationship between insurance use and factor allocation, we find that a 1% increase in insurance use leads to a 5% reduction in total labor hours used (column (1)) and a 1% increase in the value of equipment, or capital investment (column (2)).[29] The results in column (3) confirm that these changes have a jointly significant effect in altering the relative use of capital to labor. When firms are able to reduce uncertainty, they are willing to invest in durable fixed inputs rather than less specialized and more reversible inputs. The results in column (4) show that this increase in insurance use leads to a positive and statistically significant increase of 1% in an operation's enterprise value.[30] This result is consistent with

[29]While a major machinery purchase may follow a multi-year investment cycle, production requires a portfolio of such equipment that must be purchased, maintained, or upgraded regularly, as well as smaller investments in supplemental or complementary machinery.

[30]We test whether insurance use is associated with across-the-board increases in any kind of investment

predictions from Fazzari and Petersen (1993) and Karlan et al. (2014), who argue that risk management promotes firm value by allowing firms to allocate factors of production in ways that create value.

[TABLE 4 ABOUT HERE]

4.2 Risk management and returns to factors of production

In table 4, we observe a clear relationship between increases in risk management and changes in input use: capital increases and labor decreases. In this section, we explore the mechanisms that can explain this response. To do so, we use our main 2SLS specification in equations (2) and (3). We assume that these changes represent each operation's new equilibrium strategy. In a long-run equilibrium, firms allocate inputs such that the ratio of marginal products to prices is equal across all inputs. Operations therefore allocate more (less) investment to an input if it is more (less) productive or less (more) expensive. Throughout the following subsections, we explore each of these possibilities by exploring the productivity and cost of labor and capital, respectively.

4.2.1 Marginal product and price of labor

Our main findings show that increases in insurance use reduce the total amount of labor used on an agricultural operation. Theoretical arguments suggest that the effect of risk management on labor investment may vary by worker type. Importantly, ARMS reports labor use by type of worker, which allows us to measure the primary operator's labor allocation separately from the hours provided by supplemental labor. Risk management should increase the primary operator's labor, which is relatively more specialized toward agricultural work and can be considered a more irreversible and inflexible factor. Risk management also allows more of a firm's value to accrue to the owner by reducing the probability of bankruptcy.

in section 5.2.1. We find no change in investment in land, cars, or trucks. Further, we address whether the crop insurance premium subsidy could drive this observed increase in enterprise value in section 5.2.2.

Bhandari et al. (2021) and Bhandari and McGrattan (2021) posit that as managers capture more of the returns of their own labor, they increase their own labor use relative to other inputs. Moreover, capital can more easily substitute for some kinds of labor than for others, and the complementarity of capital for labor may differ across labor types.

Table 5 reports the effects of a change in insurance use on labor hours disaggregated by worker type. Primary operators, who represent the operation's upper management, actually *increase* their labor hours by 1% (column (1)). The decline in labor hours that we observe in our main results, therefore, is entirely driven by a decline in supplemental labor: these workers' hours fall by 2% (column (2)). Risk management increases the use of specialized, managerial labor while reducing the need for supplemental labor. The reduction in the operation's use of supplemental labor further suggests that this labor is more reversible–an attribute that operations value less when they are able to reduce uncertainty.

[TABLE 5 ABOUT HERE]

In our empirical setting, it is challenging to parse whether this change occurs because managerial (supplemental) labor became more (less) productive or because it became less (more) expensive. The productivity of labor, especially disaggregated by type, is difficult to measure. In terms of labor costs, the survey does not record wages by individual worker or even by worker type. Furthermore, a measure of wage alone would not capture the true cost of labor, which includes workers' opportunity costs. These are substantial, and in this context can significantly outpace workers' reported wage.

Using subsample analysis, we can provide suggestive evidence of the opportunity cost of labor. The ARMS survey records time use data for the primary operator and one supplemental worker: their spouse. Using these data, we can first disaggregate the result in table 5 that shows a reduction in supplemental labor into the hours provided by the spouse and the hours provided by other supplemental workers.[31] Then, we test how the primary operator

[31]Recall that these other workers are also often members of the primary operator's family; the spouse is asked about separately due to the nature of the survey and not as a means of distinguishing family versus non-family labor.

and his spouse's off-farm work intensity changes in response to changing insurance use, using the measure of their non-farm labor hours, which captures the time per week that is spent earning a wage or salary at a job that is unrelated to the agricultural operation.[32]

Appendix table A3 reports these results. The reduction in supplemental labor is driven by spouse labor hours, which fall by 25% (column (1)). Column (3) shows that primary operators do not change their non-agricultural labor hours. However, the spouse significantly increases time spent on non-agricultural work (column (4)).[33] Thus, the spouse reduces hours spent on agricultural tasks and reallocates those hours to non-agricultural work. Overall, these results provide suggestive evidence that at least some of the operations' supplemental labor is reallocated to non-agricultural work, which may be more productive. These workers' time may also be growing more expensive from an on-farm perspective due to the opportunity costs their time.[34]

4.2.2 Price of capital

We similarly examine our finding that risk management drives firms to increase their investment in physical capital (i.e., equipment). Risk management can reduce the price of physical capital by reducing the cost of external capital or by reducing the need for precautionary savings; the ARMS survey allows us to distinguish the two. An operation's internal financing, a proxy for precautionary savings, is captured by current spending on disaggregated

[32]While data limitations preclude a precise estimate of the value of outside earnings, studies have shown that the earnings from off-farm work in empirical contexts like ours can be substantial. For example, conditional on having an off-farm job, agricultural operators and their spouses are more likely to work in professional or management positions than the general population (Brown and Weber, 2013; Whitt et al., 2019).

[33]Due to a preponderance of zeros in these variables, we provide results in both levels (panel A) and logs (panel B). The results in logs understate the effects because they exclude observations with zero hours of a given kind of labor. The results in levels are more informative as they include all operations, regardless of whether the change in labor hours was positive, negative or zero. As the sample size in panel A indicates, there was also non-response to these questions resulting in missing observations.

[34]First, the results show that the spouse not only re-allocates time, but also increases total work hours. Second, off-farm income can enhance an operation's ability to smooth income over time, given the variability of agricultural earnings (Briggeman, 2011). More importantly, it also provides crucial non-wage benefits, particularly employer-sponsored health insurance (e.g. Huffman and Lange, 1989; Mishra et al., 2012; Brown and Weber, 2013).

equipment categories.[35] An operation's use of external financing is measured as the value of debt for equipment.[36]

Theoretical and empirical work have demonstrated how risk management expands a firm's access to external capital (Modigliani and Miller, 1958; Smith and Stulz, 1985; Bessembinder, 1991; Stulz, 1996). Crop insurance in particular increases the likelihood that short-term debt is repaid during low income years (Ifft et al., 2024). By insuring income, risk management also reduces the opportunity cost of internal funds (i.e., precautionary savings) (Froot et al., 1993; Andrade and Kaplan, 1998; Acharya et al., 2012). If insurance use lowers the cost of capital or reduces financial constraints, operations would use debt to increase capital investment. If it reduces the opportunity cost of internal capital held as precautionary savings, operations would use current spending to increase capital investment. We examine how operations use their financial resources to increase investment in equipment; table 6 reports the results.

[TABLE 6 ABOUT HERE]

Table 6 shows that firms use internal financing, or, in other words, precautionary savings, rather than external capital, to fund capital investments. The result in column (1) shows that current spending on machinery increases by 1%. By insuring revenues, risk management smooths cash flows and thus may reduce the opportunity cost of internal capital. Columns (2) through (4) report an operation's use of debt: internal spending on machinery leases, long-term debt for machinery, and an overall measure of financial solvency, respectively. None of these values change as operations increase insurance use. If, for example, our results were driven by coordinated take-up of insurance in order to secure loans for equipment (i.e.,

[35]Current spending is equal to the reported total net cost of items purchased in the current survey year. These values reflect actual cash outlays by the operation rather than debt financing, and are net of the value of trade-ins, discounts, and rebates that may have been used.

[36]Operators tend to purchase equipment through third-party collateral-based lenders and equipment loans are readily available (Newman and Tita, 2017; Byers and Ifft, 2021). Long-term loans for fixed capital and other large investments are typically self-collateralized; equipment dealers do not use crop insurance to guarantee equipment purchases. While machinery leasing does occur, investing in machinery ownership is the predominant strategy.

financial constraints), we would see equipment-specific loan volumes increase. This is not the case. Column (3) reports that operations do not increase long-term debt for machinery. Column (4) reports no significant relationship between insurance use and an operations' leverage (debt-to-asset) ratio, which serves as an overall check of whether an increase in risk management leads to an overall reduction in solvency.

These results underpin our paper's second main contribution. In these results, we document that risk management has a direct and causal role in altering an operation's production decisions that is not mediated by credit markets. Instead, we find that relaxing the revenue risk constraint allows firms to finance investments using internal capital. This finding reinforces the assertions of Karlan et al. (2014), who develop a model that identifies a unique role for insurance markets on investment allocation that is independent of capital markets. We show that this role exists even for large-scale insurance programs that are familiar to producers and in a setting with essentially complete credit and factor markets.[37]

4.2.3 Marginal product of capital

We use information on equipment spending and machinery characteristics to understand how the observed increase in equipment value relates to productivity and labor specialization. We observe additional information on the broad categories of equipment being purchased via the increase in current spending shown above in column (1) of table 6. We disaggregate the spending on all machinery into the three primary categories of machinery: tractors, self-propelled equipment, and non-self-propelled equipment; we report our results in appendix table A4. Column (1) shows that spending on tractors, which are more complementary to a primary operator's labor, does not increase. Instead, operations' spending on non-self-propelled equipment–the type of equipment more likely to replace the tasks of supplemental labor–increases by 0.5% (column (3)). This type of equipment tends to be utilitarian;[38] in

[37]We examine the relationship between crop insurance and self-reported financial constraints in section 5.2.3.

[38]For example, "high speed" planters, which are non-self-propelled, allow an operator to cover more acreage in a shorter period of time during planting.

other words, these purchases are unlikely to driven by an operator's personal preferences for upgrades and higher-end options.

In addition, we can observe the type and characteristics for all machines used on a subset of operations in our main sample using a supplemental dataset.[39] Characteristics include the machine's size, capacity, age, and horsepower. In addition to these reported characteristics, the specific machinery type can be used to classify the machines as more or less labor intensive.[40] We aggregate these machine-level data to the operation level. Labor intensity and drivetrain are measured as a proportion: the percent of machines used with that characteristic. Capacity, size, age, and horsepower are operation-level averages, taken across machines used on the field; appendix table A5 reports summary statistics.

We test whether insurance use affects the types of machines used, reflected in differences in observed physical characteristics. Characteristics such as age and horsepower could increase efficiency. Alternatively, if operations seek to reduce labor demand, there should be a decline in the labor intensity of the operation's machines. In appendix table A6 column (1), we find that an increase in insurance use is associated with a positive and significant increase in the share of machines that require less labor. Column (2) shows a corresponding reduction in the share of more labor-intensive machines. Columns (3) through (8) show that there are no other significant changes to the composition of machinery characteristics related to size, age, or horsepower.

Taken together, the results suggest that new capital investment alters the labor intensity of production but it is not driven by observed physical capacity or machine power. These changes to operations' machinery as a result of a increase in insurance use point to nuanced

[39]Each year, a subset of ARMS respondents that specialize in a particular commodity are randomly selected to complete a production-focused survey called ARMS Phase 2. Operations provide detailed information about one randomly chosen field, including the characteristics of equipment or machinery used on that field. This data set includes 1,712 operation-year observations and 856 operation-pair-of-year observations.

[40]These assessments are inherently and necessarily subjective, given the broad range of machinery characteristics across types. Further, the specific machinery type contains information not embodied in the reported characteristics. A professor of agricultural economics with over 30 years of experience as a farm operator independently ranked all machinery reported in ARMS by low, medium, or high labor intensity. This measurement complements individual machinery attributes but is not predicted by them. For example, horsepower does not predict labor efficiency.

changes in terms of how these machines supplement the amount and type of labor on an operation. These findings also complement the results in section 4.2.1: risk management allows operations to make investments in labor-saving capital and to boost the productivity of its upper management.

5 Robustness checks

In this section, we discuss alternative empirical approaches that we use to examine the robustness of our main results and rule out alternative explanations for our findings.

5.1 Alternative specifications

We use two additional empirical approaches to assess how confounding factors alter the conclusions from our 2SLS estimation. First, we use levels, instead of logs, of our outcome variables to measure how the approximation error from the log transformation affects our main results. The first stage is specified as in equation (2). We re-estimate the second stage with the outcome of interest in levels. We report the estimates in table A7. The results for all coefficients are consistent with those in table 4.

We also assess how confounding factors bias a pooled ordinary least squares (OLS) analysis. Many factors that determine an operator's choice of insurance are also likely correlated with his contemporaneous investment choices. The correlation could be positive if operators with a better understanding of financial markets use more insurance and are also more likely to invest efficiently or negative if operators with higher risk aversion use more insurance and make fewer investments. OLS estimates would include the effect of both insurance use and the factors that affect both investment and insurance use. To gauge the effects of these issues, we compare our results using the IV to results using OLS.

For completeness, we estimate this OLS specification with the log of both insurance use and the outcome of interest and with both measured in levels. The results in table A8 show

that the OLS estimates are largely consistent with the IV results. The OLS and IV estimates may differ depending on specific confounding factors in the setting. Correlations with confounding factors may drive negative OLS estimates even if the "true" effect is positive. In table A8 , the simultaneity between insurance and investment decisions may bias OLS estimates downward. Alternatively, the local average treatment effect, which is produced by 2SLS, and the average treatment effect, which is estimated with OLS, may result in differences in coefficients.

5.2 Falsification analysis

5.2.1 Other investment and credit uses

As a falsification test, we examine whether operators treat insurance as a wealth shock by increasing investment across all physical assets rather than investment in specific, potentially labor-saving, machinery. We also test for increases in credit used for non-equipment purchases.

In table A9, we report estimates from our main model using outcomes that measure investment in cars, trucks, and land. Column (1) reports a negative relationship between increased insurance use and the combined value of cars and trucks. Operations do not change their current spending on cars (column (2)) or trucks (column (3)). We also examine real estate investment: land is a fundamental productive asset that increases the size and value of an operation. If insurance drives an increase in investment overall, it would likely be reflected in an increase the value of the operation's real estate; however, this does not change (column (4)). We also test whether insurance use drives increases in long-term credit used for land (i.e., operation expansion) (column (5)) and find no effect. Finally, we test an established result in the literature, that insurance use increases the use of short-term operating credit (Ifft et al., 2015). Our results concur: column (6) reports that operations increase total short-term debt. These operating loans pay for essential short-term production

expenses.[41] Altogether, the results suggest that operators do not use insurance to increase across-the-board capital investment or to expand via credit markets.

5.2.2 Subsidy transfer and enterprise value

The increase in enterprise value we observe in table 4 is not a given *ex ante*. The premium subsidy may contribute to enterprise value in the long term; however, the contribution is likely marginal. First, operations do not directly receive the subsidy: as it is in the form of a premium discount, operations simply pay less than the actuarially fair premium. Nevertheless, there is an expected transfer to operations in the long run as legislation dictates that, over time, the indemnities paid out should be roughly equal to the total premium, where the total premium includes both the producer and government share. Although premium subsidies increased in real terms during our study period, subsidy rates decline for higher coverage levels. In other words, the marginal cost, in premiums, is higher for higher coverage levels, even after factoring in the subsidy. While it is impossible to quantify an exact measure of that expected gain, we can estimate an upper bound for a subsidy transfer during our study period and show that this transfer is not large enough to drive our results.[42]

[41] Short-term or operating loans are those with a standard maturity of one year and are typically secured by the value of crops or livestock. They are primarily used to cover the cost of variable inputs, such as seeds and fertilizer, and are paid off once revenue is realized. The "crop in the ground" serves as de facto collateral.

[42] We do this for corn, which has the highest acreage of all row crops and the highest insurance value (or per-acre revenue). Further, corn experienced higher payouts than soybeans. Nationally from 2000-2014, crop insurance for corn was very close to achieving the intended loss ratio of one: indemnities were $34.6 billion and the total premiums paid were $34.9 billion. Net indemnities are a good approximation of the actual wealth transfer, which we measure as total indemnities minus the producer-paid premiums. Net indemnities were approximately $22.88 per acre, very similar to the actual per acre premium subsidy (which approximates expected net indemnities) of $23.27 per acre. A transfer of $23 per acre for the average-sized operation in our sample (2,200 acres) is equivalent to a maximum aggregate wealth gain of about $3,400 per year. Given that the average difference between the initial and last year that we observe an operation is six years, we estimate an absolute maximum transfer of $20,000. It is difficult to compare this to the estimates of change in net worth we observe as this estimate is not a difference, as all of our coefficients of interest are. We would see a value of $20,000 only if the initial value of wealth transfer from insurance subsidies was $0, which is not the case, as every observation in our sample has some insurance use. The truly comparable value of the wealth transfer is thus some amount w with $\$0 < w < \$20{,}000$. Even at the maximum, this is a small fraction of even the observed increase in machinery value, let alone net worth.

5.2.3 Financial constraints and insurance use

We explore the possibility that higher crop insurance use is correlated with financial constraints. In most survey years these are not directly observed. However, the ARMS survey in 2014 included specific questions about an operation's financial constraints: whether an operator had been denied credit, was deterred from applying for credit, or received less credit than he had requested. This survey also included self-reported risk tolerance, recorded on a ten-point scale, and an operation's actual coverage level for the six major insurable commodity crops.

We estimate correlations between insurance use and financial constraints using an OLS specification that uses the acre-weighted coverage level as the measure of crop insurance use, along with operation-level controls[43] Table A10 reports that insurance use is unrelated to various measures of self-reported financial constraints, including an aggregate indicator of "any credit problem," which equals one if any of the three financial constraints is reported. Hence, we do not observe that financially constrained operations use higher levels of crop insurance, such that investment reallocation is unlikely to be driven by financial constraints.

6 Conclusion

This study examines whether risk management directly enables firms to reallocate investment between labor and capital. The U.S. agricultural sector provides a unified setting in which to document a cohesive connection between risk management and labor use, capital investment, cash flow smoothing, and enterprise value. Other than in experimental contexts, studies are limited in their ability to observe how risk management changes these firm-level decisions in a single setting, despite the fact that firms jointly allocate factors of production. Our empirical setting includes institutional features and rich data which we use to overcome empirical limitations to studying these connections. Program participation is

[43]These include the share of the operation's acres covered under a revenue policy, an insured commodity fixed effect, and the operator's self-reported risk tolerance.

widespread, and federal crop insurance forms the foundation for the U.S. government's farm safety net. Complete factor and credit markets also ensure we are able to isolate the impact of a change in insurance without interference from concerns about access to these markets. The USDA's operation-level survey (ARMS) includes detailed data about factor inputs, including machinery, labor use by worker type, and crop insurance use. Survey questions also include current spending, short-term and long-term borrowing, and financial constraints. Government-imposed insurance coverage limits allow us to construct an IV for changes in insurance use, based on initial coverage levels and shifts in the form of universal incentives to increase insurance use. Our causal claims are strengthened by analyses of pre-trends; institutional and managerial factors that make time-variant strategic behavior correlated with insurance and investment changes unlikely; and the staggered, randomized sampling procedure used for our dataset.

We find that increasing insurance use allows agricultural operations to increase investment in physical capital and decrease labor use. While total agricultural labor use declines, operators increase their hours while supplemental labor hours decline, suggesting a shift towards more specialized labor. Analysis of machinery characteristics provides additional evidence that these investments are labor enhancing. Further, operations use current spending to pay for new machinery, indicating a unique role of risk management separate from credit markets in factor reallocation. When evaluated as a whole, our results suggest that insurance use reduces precautionary savings and ultimately generates economic value. Hence, risk management promotes efficient factor allocation, which is a central determinant of sustainable economic growth (Arrow et al., 1961; Kuznets and Murphy, 1966).

Recent research has emphasized how technological development changes the relative prices of labor and capital, such that increasing capital and reallocating labor has generated aggregate economic growth (Autor and Dorn, 2013; Acemoglu and Restrepo, 2018; Caunedo and Kala, 2021; Mindell et al., 2023). Likewise, the economics of resource misallocation has been the focus of recent research in a variety of settings, including optimal contracts (Ai

et al., 2019) and welfare impacts of policy changes (Bhandari et al., 2021). These studies posit that income or consumption smoothing leads owners of U.S. private businesses to increase personal effort, reduce capital misallocation, and maximize production efficiency. Our results provide empirical evidence of misallocation due to risk and could be extended to other sectors or to other types of firms. For example, risk sharing may improve the quality of innovation and income insurance may improve capital and labor allocation within household-managed firms. Further, our findings that link risk management to labor reallocation suggest that estimates of the impact of risk management or policy interventions in general may be undervalued if labor use implications are unobserved, especially within household-owned-and-operated firms (Jodlowski, 2019; Agness et al., 2025). Our paper demonstrates that risk management influences these outcomes even in economies with relatively complete financial markets and in sectors that are highly mechanized. While financial constraints will continue to be relevant, the direct implications of risk management should be explored in future empirical research.

Our results have meaningful policy implications. While our analysis studies the effects of a sector-specific risk management strategy, government policies that mitigate risk and uncertainty are common: they provide assistance to areas affected by natural disasters (Barnett, 1999), they secure the risk of access to key inputs like petroleum and computer components (Rodrik, 1995; Urciuoli et al., 2014; Lind and Press, 2018), and they stabilize financial markets, corporations, and banks during recessions and market disruptions (Koch et al., 2016; Bordo and Duca, 2022). We do not claim that specific policies are optimal, as the perennial debate on the appropriate role of government support in the economy is beyond the scope of this study. Nonetheless, our findings suggest that long-term firm-level gains from factor reallocation are an important factor in the evaluation of policies that enhance risk management. Assessments of the economic value of policies and programs that impact risk management, either positively or negatively, may be underestimated if long term impacts on factor allocation are ignored.

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Tables and figures

Table 1: **Descriptive statistics: Operation characteristics**

	Mean	Std. Dev.
Crop insurance premium paid ($/acre)	7.22	18.97
Acres insured	1,148	1,568
Operator demographics		
Age	55.1	11.21
Education: High school	42%	49%
Education: Some college	30%	46%
Education: College	28%	45%
Male	98%	13%
Non-white	4%	19%
Married	89%	32%
Operation characteristics		
Acres operated	2,182	2,826
Soybean share (% acres in soybeans)	18%	23%
Corn share (% acres in corn)	16%	21%
Wheat share (% acres in wheat)	9%	16%
Revenues:		
$500,000 or more	63%	48%
$250,000 - $499,999	16%	37%
Less than $250,000	21%	41%
Primary output:		
Row crops	50%	50%
Specialty crops	18%	39%
Livestock	32%	47%
Expenses ($):		
Total cash operating expenses	1,199,330	2,842,642
Total variable expenses	1,003,550	2,567,866
Total fixed expenses	195,781	428,763
Operation-year obs.	27,790	
Number of operations	13,169	

This table summarizes characteristics of the operations in our sample from the ARMS dataset. The sample includes all operations that: (1) were observed more than once between 2000 and 2014; (2) have at least two observed years of crop insurance participation; and (3) have at least $10,000 value of production for crops with widespread crop insurance availability. All dollar values are 2013 CPI-adjusted dollars. The data dictionary in Appendix B includes either the survey question or a definition of each variable.

Table 2: **Descriptive statistics: Labor use, capital investment, and financing**

	Mean	Std. Dev.
Capital-labor substitution		
Total labor	3,606	1,635
Equipment ($)	515,415	775,287
Equipment/Total labor ($/hour)	7,145	131,172
Enterprise value ($)	2,620,865	3,068,126
Labor use (hours/year)		
Operator labor	2,801	1,039
Supplemental labor	823	1,067
Capital cost and financing		
Spending: Machinery ($)	78,694	212,673
Spending: Leasing machinery ($)	12,402	87,950
Non-real estate debt ($)	139,116	750,023
Leverage ratio	0.22	1.52
Operation-year obs.	27,790	
Number of operations	13,169	

This table summarizes capital investment, labor, and financing variables from the ARMS dataset. We report labor hours by worker type, capital investment (asset) values, and financing information for each operation-year. All dollar values are 2013 CPI-adjusted dollars. The data dictionary in Appendix B includes either the survey question or a definition of each variable.

Table 3: **Coverage ratio and insurance use**

	(1) Δ_i ln(Insurance)
Coverage ratio	-0.71***
	(0.05)
Initial insurance ($P_{i,s}$)	-0.009***
	(0.00006)
Δ_i Acres operated	0.0002
	(0.005)
Δ_i Age	-0.12
	(0.10)
Δ_i Age squared	0.001
	(0.005)
Δ_i Soybean share	1.88**
	(0.89)
Δ_i Corn share	2.45***
	(0.52)
Δ_i Wheat share	1.23***
	(0.40)
Constant	7.77***
	(2.53)
Year FE	YES
County FE	YES
Observations	14,621
R^2	0.32
F-stat	227.08

This table reports the estimates of equation (2), the first stage of the 2SLS regression specification. The sample consists of operations in the ARMS data with at least two years of insurance participation. An observation is an operation in a given pair of years (the current year t and the previous observed year s). The dependent variable, $\Delta_i$ln(Insurance), is the change in the premium paid per acre by operation i from the previous observed year s to the current year t. The coverage ratio is defined as initial premium paid per acre divided by the operation's maximum premium ($\frac{P_{i,s}}{\text{Max}P_{i,s}}$). Control variables include operator age and age squared, operation size (in acres), and shares of total production in soybeans, corn, and wheat. There are 13,169 unique operations observed anywhere from two to seven times yielding 14,621 observations with data available in years s and t. Specifications include year-of-observation fixed effects and county fixed effects. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: **Insurance use, labor use, and capital investment**

	Δ_i ln(Outcomes)			
	(1) Total labor (hours)	(2) Equipment ($)	(3) Equipment/Total labor ($/hour)	(4) Enterprise value ($)
Δ_i ln(Insurance)	-0.05***	0.01***	0.02***	0.01***
	(0.01)	(0.00)	(0.00)	(0.00)
Initial insurance ($P_{i,s}$)	-0.04***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Δ_i ln(Total labor)			-0.77***	
			(0.02)	
Operation-level controls		YES		
Year FE		YES		
County FE		YES		
Obs.	14,621	14,621	14,621	14,621
R^2	0.21	0.15	0.51	0.17

This table reports the effects of insurance use on capital and labor investment using an instrumental variable (IV) specification with first differences. The sample consists of operations in the ARMS data with at least two years of insurance participation. An observation is an operation in a given pair of years (the current year t and the previous observed year s). The coverage ratio is an instrument for $\Delta_i$ln(Insurance): the change in insurance use, measured by crop insurance premiums paid, between the two years. Initial insurance $P_{i,s}$ is the dollar value of the operation's initial insurance use in year s. Control variables include operator age and age squared, operation size (in acres), and shares of total production in soybeans, corn, and wheat. Specifications include year-of-observation fixed effects and county fixed effects. Full results are in table C1. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: **Insurance use and labor by worker type**

	Δ_i ln(Labor hours)	
	(1) Operator labor	(2) Supplemental labor
Δ_i ln(Insurance)	0.01***	-0.02*
	(0.00)	(0.01)
Initial insurance ($P_{i,s}$)	0.01***	-0.02**
	(0.00)	(0.01)
Operation-level controls	YES	
Year FE	YES	
County FE	YES	
Obs.	14,621	14,621
R^2	0.15	0.15

This table reports the effects of insurance use on the labor use of operations using an instrumental variable (IV) specification with first differences. The sample consists of operations in the ARMS data with at least two years of insurance participation. An observation is an operation in a given pair of years (the current year t and the previous observed year s). The coverage ratio is an instrument for $\Delta_i$ln(Insurance): the change in insurance use, measured by crop insurance premiums paid, between the two years. Initial insurance $P_{i,s}$ is the dollar value of the operation's initial insurance use in year s. Control variables include operator age and age squared, operation size (in acres), and shares of total production in soybeans, corn, and wheat. Specifications include year-of-observation fixed effects and county fixed effects. Full results are in table C2. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: **Insurance use and cost of capital and financing**

	Δ_i ln(Financial outcome)			
	(1) Spending: Machinery	(2) Spending: Leasing machinery	(3) Non-real estate debt	(4) Leverage ratio
Δ_i ln(Insurance)	0.01***	-0.002	0.0006	0.005
	(0.003)	-0.001	(0.002)	(0.005)
Initial insurance ($P_{i,s}$)	0.01***	-0.002*	0.002	0.004
	(0.002)	(0.001)	(0.002)	(0.004)
Operation-level controls		YES		
Year FE		YES		
County FE		YES		
Obs.	14,621	14,621	14,621	14,621
R^2	0.14	0.11	0.14	0.15

This table reports the effects of insurance use on the financial outcomes using an instrumental variable (IV) specification with first differences. The sample consists of operations in the ARMS data with at least two years of insurance participation. An observation is an operation in a given pair of years (the current year t and the previous observed year s). The coverage ratio is an instrument for $\Delta_i$ln(Insurance): the change in insurance use, measured by crop insurance premiums paid, between the two years. Initial insurance $P_{i,s}$ is the dollar value of the operation's initial insurance use in year s. Control variables include operator age and age squared, operation size (in acres), and shares of total production in soybeans, corn, and wheat. Specifications include year-of-observation fixed effects and county fixed effects. Full results are in table C3. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

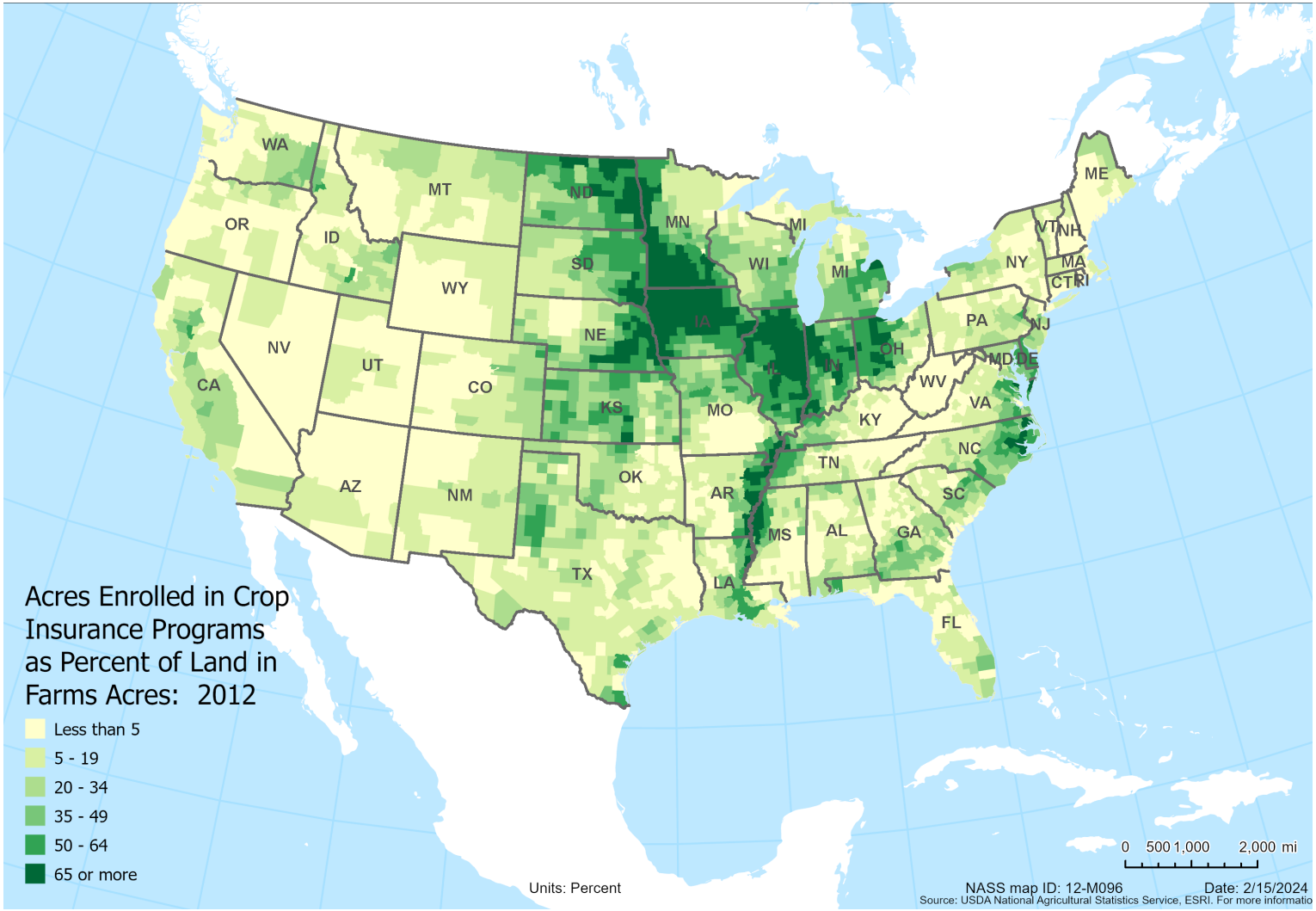


Figure 1: Geographic distribution of crop insurance use in the U.S.

Figure 1 maps the geographic distribution of program usage. Program usage is defined as the number of row crop commodity acres enrolled in the federal crop insurance program in 2012. This form of crop insurance provides explicit revenue guarantees based on current expected prices.

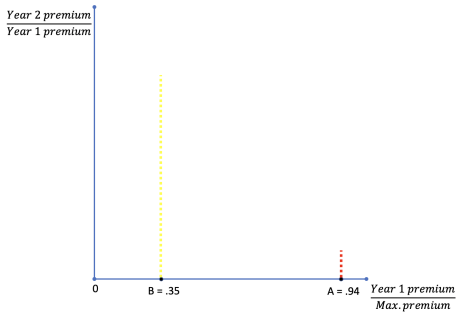
Figure 2: Coverage ratio instrumental variable



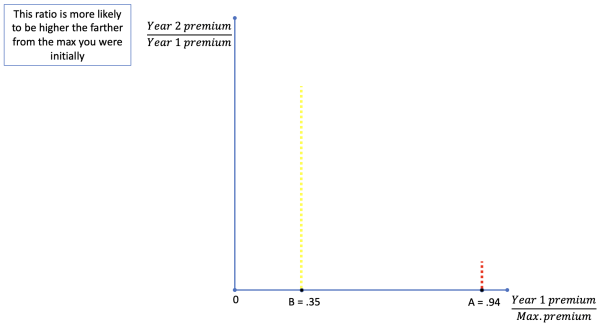
(a) Coverage ranges from 0% to the maximum coverage level, 85%. In the initial year, Operation A selects 80% coverage and Operation B selects 30% coverage.



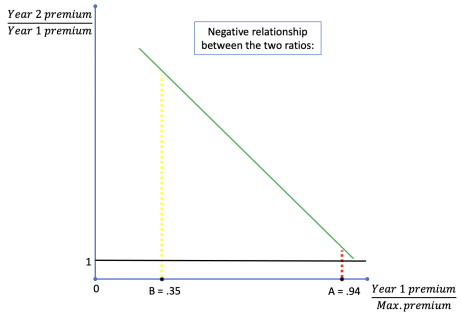
(b) The difference between B's initial coverage selection and the maximum coverage is in yellow and A's difference is in red.



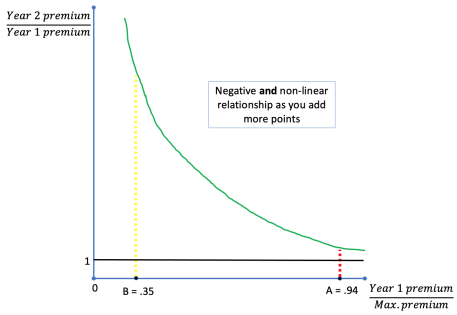
(c) We convert those differences to ratios and plot them along an axis. We then add a second axis: the ratio between the year 2 premium and the initial year (year 1) premium.



(d) The farther an operation was from the maximum in year 1, the greater the increase from year 1 to year 2 can be. We are interested in effect of increasing insurance use from year 1 to year 2.



(e) There is a negative relationship between these two ratios.



(f) As we add more points, it becomes clear that the true relationship is negative and non-linear. An operation's ability to increase coverage decreases at an increasing rate as their initial coverage choice approaches the maximum coverage.

Appendix A Additional tables

Table A1: **Determinants of initial insurance**

	(1) Coverage ratio
Capital-labor substitution:	
Total labor (hours)	0.0031
	(0.0065)
Equipment ($)	0.0043
	(0.0046)
Labor use:	
Operator labor (hours)	0.0067
	(0.0094)
Supplemental labor (hours)	0.0055
	(0.0105)
Capital cost and financing:	
Spending: Machinery ($)	-0.0036
	(0.0035)
Non-real estate debt	0.0023
	(0.0016)
Leverage ratio	-0.0015
	(0.0011)
Operation characteristics:	
Age	0.0010
	(0.0034)
Age squared	-0.0000
	(0.0000)
Education: High school	0.0101
	(0.0141)
Education: Education: Some college	0.0060
	(0.0129)
Male	-0.0434
	(0.0660)
Acres operated	-0.0000
	(0.0000)
Total non-agricultural income ($)	-0.0000
	(0.0000)
Operator off-farm work (hours)	0.0048
	(0.0106)
Spouse off-farm work (hours)	-0.0040
	(0.0063)
Total short term debt	0.0007
	(0.0011)
Real estate debt	0.0006
	(0.0010)
Revenues: $500,000 or more	0.0309*
	(0.0164)
Revenues: $250,000 - $499,999	0.0131
	(0.0156)
Primary output: Row crops	0.0439***
	(0.0164)
Primary output: Specialty crops	0.0803***
	(0.0237)
Constant	0.4827***
	(0.1158)
Year FE	YES
County FE	YES
Year × County FE	YES
Obs.	8,363
R^2	0.75

This table shows how initial insurance use relates to an operation's capital investment, labor, financing, and other characteristics. The sample consists of operations in the ARMS data with at least two years of insurance participation. The dependent variable, the coverage ratio $P_{i,s}$, is defined as initial premium paid per acre divided by the operation's maximum premium ($\frac{P_{i,s}}{\text{Max}P_{i,s}}$). The specification includes county-by-year fixed effects. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A2: **Descriptive statistics: Initial levels of dependent variables by coverage ratio terciles**

	Tercile 1		Tercile 2		Tercile 3		Tercile 2 vs. Tercile 1		Tercile 3 vs. Tercile 1	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	Norm. Diff.	Diff.	Norm. Diff
Capital-labor substitution										
Total labor (hours)	3,449	1,327	3,619	1,310	3,513	1,435	170	-0.13	64	-0.05
Equipment ($)	$422,960	$576,295	$387,108	$481,821	$367,311	$525,459	-$35,852	0.07	-$55,649	0.10
Capital/Total labor ($/hour)	$1,906	$43,263	$1,256	$46,026	$1,343	$27,253	-$650	0.01	-$563	0.02
Enterprise value ($)	$2,063,730	$3,766,236	$1,947,397	$2,934,688	$2,700,479	$4,706,930	-$116,333	0.03	$636,750	-0.15
Labor use										
Operator labor (hours)	2,846	902	2,982	921	2,882	1,017	136	-0.15	36	-0.04
Supplemental labor (hours)	643	760	703	795	669	817	60	-0.08	26	-0.03
Capital cost and financing										
Spending: Machinery ($)	$60,577	$134,650	$57,165	$140,550	$48,799	$108,840	-$3,412	0.02	-$11,778	0.10
Spending: Leasing machinery ($)	$11,276	$60,878	$8,614	$34,650	$8,063	$47,613	-$2,662	0.05	-$3,212	0.06
Non-real estate debt ($)	$893	$290,001	$95,736	$318,933	$118,466	$489,318	$94,843	-0.02	$117,573	-0.07
Leverage ratio	0.28	0.22	0.24	0.45	0.24	0.27	-0.04	0.02	-0.04	0.02
Number of operations	4,389		4,390		4,390					

This table summarizes the initial survey period characteristics of the operations across coverage ratio terciles. The values are measured at the initial year observation of each operation-year pair. The coverage ratio is defined as initial premium paid per acre divided by the operation's maximum premium ($\frac{P_{i,s}}{\text{Max}P_{i,s}}$). Tercile 1 includes the lowest coverage ratios and Tercile 3 includes the highest. The first, second, and third tercile of the coverage ratio is 0.05, 0.28, and 0.86, respectively. The difference in the means of each variable between Terciles 1 and 2 is reported in column (8) and between Terciles 1 and 3 in column (10). Columns (9) and (11) report the normalized differences in means to evaluate the statistical significance. All dollar values are 2013 CPI-adjusted dollars in $1000. Appendix B provides detailed variable definitions.

Table A3: **Insurance use and labor reallocation**

Δ_i Labor hours

	(1) Supplemental labor: Spouse	(2) Supplemental labor: Other workers	(3) Operator off-farm work	(4) Spouse off-farm work
Δ_i ln(Insurance)	-24.94**	-6.48*	1.61	58.16**
	(9.99)	(3.46)	(7.89)	(28.41)
Initial insurance ($P_{i,s}$)	3.09***	-4.50*	1.98*	-0.00
	(0.73)	(2.67)	(1.17)	(1.91)
Operation-level controls			YES	
Year FE			YES	
County FE			YES	
Obs.	14,101	11,186	5,737	10,845
R^2	0.13	0.22	0.28	0.23

Δ_i ln(Labor hours)

	(1) Supplemental labor: Spouse	(2) Supplemental labor: Other workers	(3) Operator off-farm work	(4) Spouse off-farm work
Δ_i ln(Insurance)	-0.25***	-0.05	-0.24***	0.18
	(0.10)	(0.04)	(0.01)	(0.17)
Initial insurance ($P_{i,s}$)	0.05***	-0.04	-0.07***	-0.05***
	(0.01)	(0.03)	(0.00)	(0.01)
Operation-level controls			YES	
Year FE			YES	
County FE			YES	
Obs.	8,255	3,359	191	3,892
R^2	0.29	0.55	1.00	0.31

This table reports the effects of insurance use on the labor intensity of enterprises using an instrumental variable (IV) specification with first differences. The sample consists of operations in the ARMS data with at least two years of insurance participation (all columns) and that have reported at least one year with positive working hours outside of agricultural work (columns (3) and (4)). An observation is an operation in a given pair of years (the current year t and the previous observed year s). The coverage ratio is an instrument for $\Delta_i$ln(Insurance): the change in insurance use, measured by crop insurance premiums paid, between the two years. Initial insurance $P_{i,s}$ is the dollar value of the operation's initial insurance use in year s. Control variables include operator age and age squared, operation size (in acres), and shares of total production in soybeans, corn, and wheat. Specifications include year-of-observation fixed effects and county fixed effects. Full results are in table C4 (panel A) and table C5 (panel B). Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A4: **Internal spending, disaggregated by machinery category**

	Δ_i ln(Financial outcome)		
	(1) Spending: Tractors	(2) Spending: Self-propelled	(3) Spending: Non-self-propelled
Δ_i ln(Insurance)	0.001	0.0007	0.005**
	(0.001)	(0.001)	(0.002)
Initial insurance ($P_{i,s}$)	0.001	0.0007	0.003*
	(0.001)	(0.001)	(0.002)
Operation-level controls		YES	
Year FE		YES	
County FE		YES	
Obs.	14,621	14,621	14,621
R^2	0.18	0.12	0.15

This table reports the effects of insurance use on these financial outcomes using an instrumental variable (IV) specification with first differences. The sample consists of operations in the ARMS data with at least two years of insurance participation. An observation is an operation in a given pair of years (the current year t and the previous observed year s). The coverage ratio is an instrument for $\Delta_i$ln(Insurance): the change in insurance use, measured by crop insurance premiums paid, between the two years. Initial insurance $P_{i,s}$ is the dollar value of the operation's initial insurance use in year s. Control variables include operator age and age squared, operation size (in acres), and shares of total production in soybeans, corn, and wheat. Specifications include year-of-observation fixed effects and county fixed effects. Full results are in table C6. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A5: **Descriptive statistics: Machinery characteristics**

	Mean	Std. Dev.
Less labor intensive (%)	46%	21%
More labor intensive (%)	52%	22%
Machine size (ft)	35.5	15.01
Machine capacity (bu)	613.69	304.16
Tractor age (years)	13.63	9.2
Two-wheel drive (%)	59%	33%
Four-wheel drive (%)	28%	33%
Tractor horsepower	190.81	73.04
Operation-year observations	1,712	
Number of operations	856	

This table summarizes equipment characteristics from observations in our sample, which is a subsample of 1,712 operation-year observations, drawn from the ARMS Phase 2 survey. Respondents to ARMS Phase 2 provide detailed, machine-level data which we have aggregated to the operation level as averages or proportions. Appendix B provides detailed variable definitions.

Table A6: **Insurance use and machinery characteristics**

	Δ_i ln(Machinery characteristics)							
	(1) Less labor intensive (%)	(2) More labor intensive (%)	(3) Size (ft)	(4) Capacity (bu)	(5) Age (years)	(6) Two-wheel drive (%)	(7) Four-wheel drive (%)	(8) Horsepower
Δ_i ln(Insurance)	0.04***	-0.02	0.01	0.01	-0.03	0.01	-0.02	-0.01
	(0.02)	(0.01)	(0.01)	(0.04)	(0.05)	(0.02)	(0.04)	(0.02)
Initial insurance ($P_{i,s}$)	0.003*	0.0006	0.002	0.003	-0.0007	0.003	-0.0009	-0.0005
	(0.002)	(0.007)	(0.07)	(0.005)	(0.005)	(0.006)	(0.004)	(0.002)
Controls				YES				
Year FE				YES				
County FE				YES				
Obs.	856	856	666	758	518	518	518	517
R^2	0.33	0.31	0.36	0.21	0.48	0.42	0.31	0.41

This table reports the effects of insurance use on the characteristics of an operation's equipment using an instrumental variable (IV) specification with first differences. The sample consists of a subset of operations in the ARMS data with at least two years of insurance participation and two years of inclusion in the supplemental ARMS Phase 2 survey. An observation is an operation in a given pair of years (the current year t and the previous observed year s). The coverage ratio is an instrument for $\Delta_i$ln(Insurance): the change in insurance use, measured by crop insurance premiums paid, between the two years. Initial insurance $P_{i,s}$ is the dollar value of the operation's initial insurance use in year s. Control variables include operator age and age squared, operation size (in acres), and shares of total production in soybeans, corn, and wheat. Specifications include year-of-observation fixed effects and county fixed effects. Full results are in table C7. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A7: **Insurance use, labor use, and capital investment, in levels**

	Δ_i **Outcomes**			
	(1) Total labor (hours)	(2) Equipment ($)	(3) $\frac{\text{Equipment}}{\text{Total labor}}$ ($/hours)	(4) Enterprise value ($)
Δ_i ln(Insurance)	-14.31***	9,908.45***	1,332.12	19,506.94***
	(5.16)	(2,026.42)	(1,457.64)	(7,111.46)
Initial insurance ($P_{i,s}$)	-12.44***	6,000.79***	1,189.66	9,216.27*
	(4.08)	(1,438.28)	(1,218.05)	(5,551.00)
Total labor$_s \times (-1)$			-2.91***	
			(0.54)	
Total labor$_t$			-8.84***	
			(1.70)	
Operation-level controls		YES		
Year FE		YES		
County FE		YES		
Obs.	14,621	14,621	14,621	14,621
R^2	0.16	0.12	0.20	0.16

This table reports the effects of insurance use on capital and labor investment using an instrumental variable (IV) specification with first differences. The sample consists of operations in the ARMS data with at least two years of insurance participation. An observation is an operation in a given pair of years (the current year t and the previous observed year s). The coverage ratio is an instrument for $\Delta_i$ln(Insurance): the change in insurance use, measured by crop insurance premiums paid, between the two years. Initial insurance $P_{i,s}$ is the dollar value of the operation's initial insurance use in year s. Control variables include operator age and age squared, operation size (in acres), and shares of total production in soybeans, corn, and wheat. Specifications include year-of-observation fixed effects and county fixed effects. Full results are in table C8. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A8: **Pooled OLS: Insurance use, labor use, and capital investment**

	ln(Outcomes)			
	(1) Total labor (hours)	(2) Equipment ($)	(3) $\frac{\text{Equipment}}{\text{Total labor}}$ ($/hours)	(4) Enterprise value ($)
ln(Insurance)	0.01	0.03***	0.03**	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
ln(Total labor)			-0.96***	
			(0.01)	
Operation-level controls		YES		
Year FE		YES		
Operation FE		YES		
Obs.	27,790	27,790	27,790	27,790
R^2	0.03	0.22	0.14	0.35

	Outcomes			
	(1) Total labor (hours)	(2) Equipment ($)	(3) $\frac{\text{Equipment}}{\text{Total labor}}$ ($/hours)	(4) Enterprise value ($)
Insurance	1.57	1,075.55*	39.71	5,346.31**
	(1.12)	(566.17)	(43.14)	(2,240.79)
Total labor			-9.42***	
			(0.43)	
Operation-level controls		YES		
Year FE		YES		
Operation FE		YES		
Obs.	27,790	27,790	27,790	27,790
R^2	0.06	0.12	0.01	0.06

This table reports the effects of insurance use on the capital and labor investment of operations using a pooled OLS specification. The sample consists of operations in the ARMS data with at least two years of insurance participation. Each observation represents a operation-year pair. Control variables include operator age and age squared, operation size (in acres), and shares of total production in soybeans, corn, and wheat. Specifications include year-of-observation fixed effects and operation fixed effects. Full results are in table C9. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A9: **Placebo analysis: Insurance use, other investment, and financing**

	Δ_i ln(Financial outcomes)					
	(1) Investment: Cars and trucks	(2) Spending: Cars	(3) Spending: Trucks	(4) Investment: Real estate	(5) Real estate debt	(6) Total short term debt
Δ_i ln(Insurance)	-0.04***	0.00	0.00	0.01	0.00	0.01***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)	(0.003)
Initial insurance ($P_{i,s}$)	-0.04***	0.00	0.00	0.01	-0.00	0.005**
	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)	(0.002)
Operation-level controls			YES			
Year FE			YES			
County FE			YES			
Obs.	14,621	14,621	14,621	14,621	14,621	14,621
R^2	0.17	0.13	0.14	0.13	0.13	0.13

This table reports the effects of insurance use on non-machinery investment and financing using an instrumental variable (IV) specification with first differences. The sample consists of operations in the ARMS data with at least two years of insurance participation. An observation is an operation in a given pair of years (the current year t and the previous observed year s). The coverage ratio is an instrument for $\Delta_i$ln(Insurance): the change in insurance use, measured by crop insurance premiums paid, between the two years. Initial insurance $P_{i,s}$ is the dollar value of the operation's initial insurance use in year s. Control variables include operator age and age squared, operation size (in acres), and shares of total production in soybeans, corn, and wheat. We report estimates with year-of-observation fixed effects and county fixed effects. Full results are in table C10. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A10: **Insurance use and financial constraints**

	(1) Denied credit	(2) Deterred from credit use	(3) Any credit problem
Average insurance coverage	0.0005	0.0006	0.001
	(0.0009)	(0.0005)	(0.0009)
Share of acres insured	0.02	-0.002	0.02
	(0.02)	(0.01)	(0.02)
Risk tolerance	0.02***	-0.004**	0.01***
	(0.003)	(0.002)	(0.003)
Operation-level controls		YES	
State FE		YES	
Obs.	4,393	3,983	4,393
R^2	0.05	0.01	0.05

This table reports an analysis of an operator's self-reported credit constraints as a function of crop insurance use and risk tolerance. The sample includes operations that were surveyed in the 2014 ARMS survey. An observation is an operation in 2014 ($t = 2014$). Our variable of interest, crop insurance, is measured by acre-weighted average revenue coverage level. Controls include the share of acres covered, the operator's self-reported risk tolerance, an indicator for each of the insured commodities, operator demographics, non-agricultural income, the size of the operation, the fraction of production in soybeans, corn, and wheat, and indicators for the operation's primary output and revenue class. Full results are in table C11. Robust standard errors appear in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix B Data dictionary and panel creation

Appendix B.1 Data dictionary

Variable	Definition
Acres insured	Number of acres covered by a crop insurance plan
Age	Operator age in years
Any credit problem	An indicator equal to one if the operator reported having any credit problems (either being denied credit or deterred from seeking credit)
Average insurance coverage	Average insurance coverage level (across crops) used on an operation; only observed in 2014
Coverage level	Coverage level refers to the share or percentage of expected revenue that is guaranteed by crop insurance policy. Coverage levels are typically 50% to 85%, in 5% increments.
Coverage limit	The maximum coverage level of 85% imposed by the federal government creates a maximum coverage level that is the basis for our instrumental variable strategy.
Denied credit	An indicator equal to one for positive response to the survey question: "Was a request for credit or loan application for agricultural purposes either turned down or were you not given as much credit as you applied for in 2014?"
Deterred from credit use	An indicator equal to one if the operator reported that he did not apply for new loans or additional credit in 2014 because: 1) he "expected to be unable to obtain new or additional credit," 2) the "high costs associated with loan applications," or 3) the "risks associated with debt"
Education: College	Operator's highest educational attainment is completing a 4-year college degree or more
Education: High school	Operator's highest educational attainment is completing high school or less
Education: Some college	Operator's highest educational attainment is some college (without completing a 4-year degree), including a 2-year degree
Enterprise value	The sum of the agricultural operation's net worth plus the household's net worth, measured in 2013 $
Equipment	Market value of all machinery owned by the operation: tractors, self-propelled, and non-self-propelled equipment, measured in 2013 $
Four-wheel drive (%)	Percent of machines used on the operation that have four-wheel drive
Investment: Cars and trucks	Market value of all cars and trucks owned by the operation, measured in 2013 $

Investment: Real estate	Market value of all real estate owned by the operation, measured in 2013 $
Less labor intensive (%)	Percent of machines used on the operation classified as having low labor requirements
Leverage ratio	Debt (total financial debt) to asset (total farm assets) ratio
Machine capacity (bushels)	Average capacity of machines used on the operation, measured in bushels
Machine size (feet)	Average size, in feet, of machines used on the operation
Male	Indicator variable equal to one if the operator is male
Married	Indicator variable equal to one if the operator reports having a spouse
More labor intensive (%)	Percent of machines used on the operation classified as having high labor requirements
Non-real estate debt	Total amount of debt held by the operation with a maturity longer than one year that is not financing real estate, measured in 2013 $
Non-white	Indicator variable equal to one if the operator's self-described race is anything other than white/Caucasian
Operator labor	Hours per year worked by the primary operator on the agricultural operation
Operator off-farm work	Hours per year worked by the primary operator at a job or business unrelated to the agricultural operation
Primary operator	The primary manager and the owner; responsible for day to day and long term business decisions
Primary output	Categorical variable based on which commodity provides the majority of sales revenue for the operation
Real estate debt	Total amount of debt held by the operation with a maturity longer than one year, that is financing real estate, measured in 2013 $
Revenues	Categorical variable representing bins of revenue (i.e., gross value of sales of agricultural products) levels
Risk tolerance	Response to survey question: "Are you generally a person willing to take risks or do you try to avoid taking risks? Please mark one box on the scale below where the value "0" means "not at all willing to take risks" and the value "10" means "fully willing to take risks."
Spending: Cars	Total net cost (after deducting the value of trade-ins, rebates, and discounts) of the cars purchased for the operation in the survey year, measured in 2013 $
Spending: Leasing machinery	Amount spent in the survey year for renting or leasing farm machinery (including tractors, self-propelled, and non-self propelled machines), measured in 2013 $
Spending: Machinery	Total net cost (after deducting the value of trade-ins, rebates, and discounts) of the machines purchased for the operation in the survey year, measured in 2013 $

Spending: Non-self-propelled machinery	Total net cost (after deducting the value of trade-ins, rebates, and discounts) of the non-self-propelled machines purchased for the operation in the survey year, measured in 2013 $. These machines either connect to another machine or are stationary.
Spending: Self-propelled machinery	Total net cost (after deducting the value of trade-ins, rebates, and discounts) of the self-propelled machines purchased for the operation in the survey year, measured in 2013 $. These machines have an internal engine, such as a combine.
Spending: Tractors	Total net cost (after deducting the value of trade-ins, rebates, and discounts) of the tractors purchased for the operation in the survey year, measured in 2013 $
Spending: Trucks	Total net cost (after deducting the value of trade-ins, rebates, and discounts) of the trucks (including pickups, SUVs, vans, campers, and buses) purchased for the operation in the survey year, measured in 2013 $
Supplemental labor	Hours per year worked by the workers who are not the primary operator on the agricultural operation
Spouse off-farm work	Hours per year worked by the primary operator's spouse at a job or business unrelated to the agricultural operation
Total cash operating expenses	Cash operating expenses necessitate a cash outlay, in order to distinguish them from non-cash expenses (e.g., animal feed that is grown on the operation), measured in 2013 $
Total fixed expenses	The sum of property and real estate taxes, interest, insurance, and rental and lease payments, measured in 2013 $
Total labor	Hours per year worked by all workers, regardless of type, on the agricultural operation
Total short term debt	The total amount ($) of debt taken on with the intention of being repaid within a year, measured in 2013 $. It is the sum of the debt taken out and repaid plus the amount of debt outstanding that was intended to be repaid in the current year.
Total variable expenses	The sum of purchased livestock, feed, other livestock expenses, seed and plant expenses, fertilizer, labor, fuel, maintenance and repair, custom work, utilities, and other variable expenses not listed here, measured in 2013 $
Tractor age (years)	Average age of tractors used on the operation in years, measured from the year it was made
Tractor horsepower	Average horsepower of the tractors used on the operation
Two-wheel drive (%)	Percent of machines used on the operation that have two-wheel drive

Appendix B.2 Sample construction

There are a total of 110,591 operation-year observations in the full ARMS panel, from 1996 to 2014. These represent 46,976 unique operations; the number of years in which an operation is observed is between two and nine. The number of farms by number of appearances in the full ARMS panel sample is available in column (1) of table B2.

The first sample restriction that we make is dropping the observations prior to 2000; before this year, operations did not report the amount they spent on crop insurance premiums in the survey. This leaves 98,650 observations. After these 1996-1999 observations are dropped, there are now operations that appear only once in our sample and therefore must be dropped. Doing so results in a sample of 92,272 operation-year observations, representing 39,827 unique observations. Their breakdown by number of times observed can be found in column (2) of table B2.

Next, in order to create a sample of operations for which crop insurance was likely to be a viable option throughout our study period, we limit the sample further to operations with at least $10,000 value of production of crops with widespread crop insurance availability. This eliminates operations that specialize in horticulture, tree crops, and livestock. In addition, operations that never use crop insurance, even if they specialize in a commodity row crop for which it is readily available, are likely to be very different from operations that do. Therefore, we also eliminate operations that record not participating in federal crop insurance programs in any year they are observed in ARMS, as well as operations that are in counties without a crop insurance policy for the crops they produce. Without such a policy available, it is impossible to construct the coverage ratio instrumental variable, as there is no value for the maximum premium. These three restrictions decrease the number of operation-year observations in our analysis to 41,727. After these observations are dropped, we once again eliminate any operation that now appears in our sample only once. The result is 33,959 observations representing 13,910 unique operations; the detailed breakdown for this "restricted" panel can be found in column (3) of table B2.

Table B2: **Sample construction: Number of operations by number of appearances in sample**

Number of appearances	(1) Full panel: Number of operations	(1) Full panel: Percent of sample	(2) 2000-2014 panel: Number of operations	(2) 2000-2014 panel: Percent of sample	(3) "Restricted" panel: Number of operations	(3) "Restricted" panel: Percent of sample
2	34,912	63.14%	30,273	65.62%	9,403	55.38%
3	8,666	23.15%	7,152	23.25%	3,228	28.52%
4	2,475	8.95%	1,851	8.02%	993	11.70%
5	713	3.22%	456	2.47%	230	3.39%
6	170	0.92%	81	0.53%	47	0.83%
7	37	0.23%	12	0.09%	7	0.14%
8	2	0.01%	2	0.02%	2	0.05%
9	1	0.01%	-	-%	-	-%
Total:	46,976	100.0%	39,827	100.0%	13,910	100.0%
Number of observations:	110,591		98,650		33,959	

The final sample restrictions we apply eliminate the 3,543 observations that have a missing value for crop insurance premium paid, bringing the sample for analysis to 29,639 operation-year observations after eliminating the operations now only observed once. We then drop operations who do not report a non-zero premium paid in at least two years, resulting in 1,849 fewer observations. Due to the construction of our instrument, it is not possible to use operations that report $0 premiums as we cannot apply the natural log. Dropping these observations and then ensuring that every operation is still observed at least twice results in the final sample of 27,790 operation-year observations, representing 13,169 unique operations. The breakdown by number of times observed for the final sample is available below in table B3. Because our primary specifications use data at the operation-pair-of-years level, the final sample for estimation is made up of the single difference contributed by the operations observed in two years plus the two differences from the operations observed in three years, plus the three differences from the operations observed in four years, and so on. Our main estimating sample is thus comprised of 14,619 operation-pair-of-year observations.

Table B3: **Final sample: Number of operations by number of appearances in sample**

Number of appearances	Final panel: Number of operations	Final panel: Percent of sample
2	11,925	90.55%
3	1,060	8.05%
4	168	6.48%
5	10	1.28%
6	4	0.03%
7	2	0.02%
8	-	-%
9	-	-%
Total:	13,169	100.0%
Number of observations:	27,790	

Appendix C Full tables

Appendix C.1 Full tables for results in main text & Appendix A

Table C1: **Full results: Insurance use, labor use, and capital investment**

	Δ_i ln(Outcomes)			
	(1) Total labor (hours)	(2) Equipment ($)	(3) $\frac{\text{Investment}}{\text{Total labor}}$ ($/hour)	(4) Enterprise value ($)
Δ_i ln(Insurance)	-0.05***	0.01***	0.02***	0.01***
	(0.01)	(0.00)	(0.00)	(0.003)
Initial insurance ($P_{i,s}$)	-0.04***	0.01***	0.01***	0.007***
	(0.00)	(0.00)	(0.00)	(0.002)
Δ_i Acres operated	-0.00	0.00***	0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Δ_i Age	-0.04***	0.01*	0.01**	0.01**
	(13.09)	(0.01)	(0.01)	(0.01)
Δ_i Age squared	-0.43***	0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Δ_i Soybean share	-0.50***	0.09	0.11*	0.24***
	(0.10)	(0.05)	(0.06)	(0.05)
Δ_i Corn share	-0.20*	0.37***	0.33***	0.22***
	(0.11)	(0.06)	(0.07)	(0.06)
Δ_i Wheat share	-0.36***	0.08	0.09	-0.03
	(0.14)	(0.07)	(0.08)	(0.07)
Δ_i ln(Total labor)			-0.77***	
			(0.02)	
Constant	1.36***	0.20	0.07	-0.31
	(0.35)	(0.40)	(0.40)	(0.48)
Year FE			YES	
County FE			YES	
Obs.	14,621	14,621	14,621	14,621
R^2	0.21	0.15	0.51	0.17

This table reports the full set of coefficients for the analysis in table 4 of the effects of insurance use on the capital and labor investment using an instrumental variable (IV) specification with first differences. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C2: **Full results: Insurance use and labor by worker type**

	Δ_i ln(Labor hours)	
	(1) Operator labor	(2) Supplemental labor
Δ_i ln(Insurance)	0.01***	-0.02*
	(0.00)	(0.01)
Initial insurance ($P_{i,s}$)	0.01***	-0.02**
	(0.00)	(0.01)
Δ_i Acres operated	0.00	-0.00**
	(0.00)	(0.00)
Δ_i Age	-0.03***	-0.03
	(0.01)	(0.02)
Δ_i Age squared	0.00***	0.00
	(0.00)	(0.00)
Δ_i Soybean share	-0.05	-0.06
	(0.05)	(0.22)
Δ_i Corn share	0.09	0.16
	(0.07)	(0.25)
Δ_i Wheat share	0.13*	-0.21
	(0.08)	(0.28)
Constant	0.56***	1.96
	(0.19)	(1.44)
Year FE	YES	
County FE	YES	
Obs.	14,621	14,621
R^2	0.15	0.15

This table reports the full set of coefficients for the analysis in table 5 of the effects of insurance use on the labor use of operations using an instrumental variable (IV) specification with first differences. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C3: **Full results: Insurance use and cost of capital and financing**

	Δ_i ln(Financial outcome)			
	(1) Spending: Machinery	(2) Spending: Leasing machinery	(3) Non-real estate debt	(4) Leverage ratio
Δ_i ln(Insurance)	0.01***	-0.002	0.0006	0.005
	(0.00)	-0.001	(0.002)	(0.005)
Initial insurance ($P_{i,s}$)	0.01***	-0.002*	0.002	0.004
	(0.00)	(0.001)	(0.002)	(0.004)
Δ_i Acres operated	0.00***	0.00***	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Δ_i Age	0.00	-0.01***	0.00	-0.01
	(0.01)	(0.00)	(0.00)	(0.01)
Δ_i Age squared	-0.00	0.00***	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Δ_i Soybean share	-0.00	-0.00	-0.04	-0.30***
	(0.05)	(0.03)	(0.04)	(0.09)
Δ_i Corn share	0.09	0.07**	0.11**	-0.00
	(0.06)	(0.04)	(0.05)	(0.10)
Δ_i Wheat share	0.14*	0.02	0.11**	0.28**
	(0.07)	(0.04)	(0.05)	(0.13)
Constant	0.54	-0.06	-0.22	0.41
	(0.57)	(0.17)	(0.34)	(0.52)
Year FE		YES		
County FE		YES		
Obs.	14,621	14,621	14,621	14,621
R^2	0.14	0.11	0.14	0.15

This table reports the full set of coefficients for the analysis in table 6 of the effects of insurance use on the cost of capital and sources of financing using an instrumental variable (IV) specification with first differences. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C4: **Full results: Insurance use and labor reallocation, in levels (panel A)**

	Δ_i Labor hours			
	(1) Supplemental labor: Spouse	(2) Supplemental labor: Other workers	(3) Operator off-farm work	(4) Spouse off-farm work
Δ_i ln(Insurance)	-24.94**	-6.48*	1.61	58.16**
	(9.99)	(3.46)	(7.89)	(28.41)
Initial insurance ($P_{i,s}$)	3.09***	-4.50*	1.98*	-0.00
	(0.73)	(2.67)	(1.17)	(1.91)
Δ_i Acres operated	0.00	-0.01**	0.01***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
Δ_i Age	17.67 ***	3.32	0.85	-9.61
	(3.31)	(7.06)	(4.24)	(6.50)
Δ_i Age squared	-0.16***	-0.03	-0.00	0.17***
	(0.03)	(0.06)	(0.04)	(0.06)
Δ_i Soybean share	19.36	84.37	76.72*	-193.37***
	(33.58)	(59.37)	(44.01)	(66.95)
Δ_i Corn share	16.29	35.84	12.50	124.01
	(41.73)	(70.38)	(51.15)	(77.19)
Δ_i Wheat share	-140.60***	-75.85	-127.17**	36.97
	(49.16)	(77.46)	(56.43)	(84.90)
Constant	-70.16	2,113.20***	-788.78	-921.55
	(170.43)	(437.24)	(561.92)	(728.72)
Year FE		YES		
County FE		YES		
Obs.	14,101	11,186	5,737	10,845
R^2	0.13	0.22	0.28	0.23

This table reports the full set of coefficients for the analysis in panel A of table A3 of the effects of insurance use on the labor intensity of enterprises using an instrumental variable (IV) specification with first differences. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C5: **Full results: Insurance use and labor reallocation (panel B)**

	Δ_i ln(Labor hours)			
	(1) Supplemental labor: Spouse	(2) Supplemental labor: Other workers	(3) Operator off-farm work	(4) Spouse off-farm work
Δ_i ln(Insurance)	-0.25***	-0.05	-0.24***	0.18
	(0.10)	(0.04)	(0.01)	(0.17)
Initial insurance ($P_{i,s}$)	0.05***	-0.04	-0.07***	-0.05***
	(0.01)	(0.03)	(0.00)	(0.01)
Δ_i Acres operated	-0.00***	0.00	-0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Δ_i Age	0.00	0.04	0.51***	0.06
	(0.03)	(0.07)	(0.01)	(0.04)
Δ_i Age squared	-0.00	-0.00	-0.01***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Δ_i Soybean share	0.46	0.45	-3.67***	0.06
	(0.35)	(0.71)	(0.09)	(0.33)
Δ_i Corn share	0.06	1.43*	-10.77***	0.46
	(0.38)	(0.81)	(0.18)	(0.40)
Δ_i Wheat share	-0.78*	-2.40**	-2.04***	-0.36
	(0.40)	(1.02)	(0.05)	(0.45)
Constant	7.50***	11.86***	-4.85***	-10.75***
	(0.92)	(2.70)	(0.08)	(1.06)
Year FE		YES		
County FE		YES		
Obs.	8,255	3,359	191	3,892
R^2	0.29	0.55	1.00	0.31

This table reports the full set of coefficients for the analysis in panel B of table A3 of the effects of insurance use on the labor intensity of enterprises using an instrumental variable (IV) specification with first differences. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C6: **Full results: Internal spending, disaggregated by machinery category**

	Δ_i ln(Financial outcome)		
	(1) Spending: Tractors	(2) Spending: Self-propelled	(3) Spending: Non-self-propelled
Δ_i ln(Insurance)	0.001	0.0007	0.005**
	(0.001)	(0.001)	(0.002)
Initial insurance ($P_{i,s}$)	0.001	0.0007	0.003*
	(0.001)	(0.001)	(0.002)
Δ_i Acres operated	0.00***	0.00	0.00***
	(0.00)	(0.00)	(0.00)
Δ_i Age	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)
Δ_i Age squared	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)
Δ_i Soybean share	-0.01	0.01	0.06*
	(0.02)	(0.02)	(0.04)
Δ_i Corn share	-0.01	0.04*	0.06
	(0.03)	(0.02)	(0.05)
Δ_i Wheat share	0.02	0.01	0.17***
	(0.03)	(0.03)	(0.05)
Constant	-0.10	-0.03	1.04**
	(0.35)	(0.07)	(0.49)
Year FE		YES	
County FE		YES	
Obs.	14,621	14,621	14,621
R^2	0.18	0.12	0.15

This table reports the full set of coefficients for the analysis in table A4 of the effects of insurance use on the disaggregated categories of internal spending using an instrumental variable (IV) specification with first differences. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C7: **Full results: Insurance use and machinery characteristics**

	Δ_i ln(Machinery characteristics)							
	(1) Less labor intensive (%)	(2) More labor intensive (%)	(3) Size (ft)	(4) Capacity (bu)	(5) Age (years)	(6) Two-wheel drive (%)	(7) Four-wheel drive (%)	(8) Horsepower
Δ_i ln(Insurance)	0.04***	-0.02	0.01	0.01	-0.03	0.01	-0.02	-0.01
	(0.02)	(0.01)	(0.01)	(0.04)	(0.05)	(0.02)	(0.04)	(0.02)
Initial insurance ($P_{i,s}$)	0.003*	0.0006	0.002	0.003	-0.0007	0.003	-0.0009	-0.0005
	(0.002)	(0.007)	(0.07)	(0.005)	(0.005)	(0.006)	(0.004)	(0.002)
Δ_iAcres operated	0.00	-0.00	0.00*	-0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δ_iAge	-0.00	-0.00	0.00	-0.01	0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Δ_iAge squared	0.00	0.00	0.00	0.00	-0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δ_iSoybean share	0.02	-0.03	0.04	-0.20	0.05	0.01	0.01	0.01
	(0.03)	(0.03)	(0.04)	(0.17)	(0.04)	(0.02)	(0.02)	(0.01)
Δ_iCorn share	0.06	-0.06*	0.02	0.15	-0.01	-0.01	-0.00	-0.01
	(0.06)	(0.03)	(0.04)	(0.14)	(0.02)	(0.01)	(0.01)	(0.01)
Δ_iWheat share	0.05	0.02	-0.00	0.01	0.02	-0.01	0.02	0.01
	(0.04)	(0.03)	(0.03)	(0.10)	(0.03)	(0.01)	(0.02)	(0.01)
Constant	0.02	0.05	-0.05	0.29	-0.00	0.02	-0.06	-0.02
	(0.08)	(0.07)	(0.06)	(0.23)	(0.10)	(0.03)	(0.05)	(0.03)
Year FE				YES				
County FE				YES				
Obs.	856	856	666	758	518	518	518	517
R^2	0.33	0.31	0.36	0.21	0.48	0.42	0.31	0.41

This table reports the full set of coefficients for the analysis in table A6 of the characteristics of an operation's equipment using an instrumental variable (IV) specification with first differences. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C8: **Full results: Insurance use, labor use, and capital investment, in levels**

	Outcomes			
	(1) Total labor (hours)	(2) Equipment ($)	(3) $\frac{\text{Equipment}}{\text{Total labor}}$ ($/hour)	(4) Enterprise value ($)
Δ_i ln(Insurance)	-14.31***	9,908.45***	1,332.12	19,506.94***
	(5.16)	(2,026.42)	(1,457.64)	(7,111.46)
Initial insurance ($P_{i,s}$)	-12.44***	6,000.79***	1,189.66	9,216.27*
	(4.08)	(1,438.28)	(1,218.05)	(5,551.00)
Δ_iAcres operated	-0.00	36.25***	0.99*	65.61***
	(0.01)	(4.27)	(0.51)	(11.01)
Δ_iAge	-11.47	13,692.46***	956.80***	62,456.16***
	(10.11)	(3,847.57)	(316.67)	(12,985.24)
Δ_iAge squared	0.04	-139.92 ***	-9.29***	-511.74***
	(0.09)	(33.56)	(3.16)	(114.51)
Δ_iSoybean share	-220.25**	52,228.95	-13,962.10	307,456.60***
	(90.04)	(32,205.09)	(8,956.12)	(118,058.75)
Δ_iCorn share	57.29	240,209.51***	-10,125.77	890,086.03***
	(106.00)	(39,088.99)	(16,650.23)	(146,766.05)
Δ_iWheat share	-71.73	49,544.15	-11,238.97	-64,148.88
	(123.54)	(48,447.78)	(11,985.17)	(169,525.55)
Total labor$_s \times (-1)$			-2.91***	
			(0.54)	
Total labor$_t$			-8.84***	
			(1.70)	
Constant	204.92	-136,672.19	-19,217.14*	-1,945,343.53**
	(585.87)	(249,512.35)	(11,435.88)	(846,610.49)
Year FE		YES		
County FE		YES		
Obs.	14,621	14,621	14,621	14,621
R^2	0.16	0.12	0.20	0.16

This table reports the full set of coefficients for the analysis in table A7 of the effects of insurance use on capital and labor investment using an instrumental variable (IV) specification with first differences. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C9: **Full results: Pooled OLS: Insurance use, labor use, and capital investment**

ln(Outcomes)

	(1) Total labor (hours)	(2) Equipment ($)	(3) $\frac{\text{Investment}}{\text{Total labor}}$ ($/hour)	(4) Enterprise value ($)
ln(Insurance)	0.01	0.03***	0.03**	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
ln(Total labor)			-0.96***	
			(0.01)	
Acres operated	0.00***	0.00***	0.0001***	0.00***
	(0.00)	(0.00)	(0.00001)	(0.00)
Age	-0.02***	0.07***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
Age squared	0.00***	-0.00***	0.0005***	-0.00***
	(0.00)	(0.00)	(0.0001)	(0.00)
Soybean share	-0.03	-0.14*	-0.16**	-0.17**
	(0.06)	(0.08)	(0.08)	(0.07)
Corn share	0.26***	0.21**	0.22**	0.04
	(0.10)	(0.09)	(0.09)	(0.09)
Wheat share	0.03	-0.11	-0.05	-0.26***
	(0.08)	(0.08)	(0.08)	(0.09)
Constant	8.42***	10.07***	9.99***	11.78***
	(0.26)	(0.25)	(0.26)	(0.29)
Year FE		YES		
Operation FE		YES		
Obs.	27,790	27,790	27,790	27,790
R^2	0.03	0.22	0.54	0.35

Outcomes

	(1) Total labor (hours)	(2) Equipment ($)	(3) $\frac{\text{Investment}}{\text{Total labor}}$ ($/hour)	(4) Enterprise value ($)
Insurance	1.57	1,075.55*	39.71	5,346.31**
	(1.12)	(566.17)	(43.14)	(2,240.79)
Total labor			-9.42***	
			(0.43)	
Acres operated	0.13***	97.03 ***	-0.01	362.93***
	(0.01)	(11.30)	(0.50)	(82.25)
Age	-0.07	22,637.29***	1,762.82***	79,181.80*
	(11.10)	(4,968.47)	(455.02)	(43,986.11)
Age squared	0.01	-199.07***	-18.23***	-634.29*
	(0.10)	(44.47)	(4.00)	(356.84)
Soybean share	25.35	58,992.98	-2,202.88	-354,423.60**
	(88.72)	(36,926.11)	(4,191.59)	(154,768.07)
Corn share	262.98**	299,580.78***	-9,769.16**	331,787.24
	(105.59)	(45,650.68)	(4,727.84)	(214,212.37)
Wheat share	15.36	11,149.25	-348.53	-531,086.25**
	(100.25)	(39,274.04)	(4,628.86)	(212,490.06)
Constant	2,910.94***	-572,465.90***	-38,318.11***	-1,473,936.51
	(308.13)	(137,078.54)	(12,693.59)	(1,229,727.03)
Year FE		YES		
Operation FE		YES		
Obs.	27,790	27,790	27,790	27,790
R^2	0.06	0.12	0.05	0.06

This table reports the full set of coefficients for the analysis in table A8 of the effects of insurance use on the capital and labor investment of operations using a pooled OLS specification. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C10: **Full results: Placebo analysis: Insurance use, other investment, and financing**

	Δ_i ln(Financial outcome)					
	(1) Investment: Cars and trucks	(2) Spending: Cars	(3) Spending: Trucks	(4) Investment: Real estate	(5) Real estate debt	(6) Total short term debt
Δ_i ln(Insurance)	-0.04***	0.00	0.00	0.01	0.00	0.01***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)
Initial insurance ($P_{i,s}$)	-0.04***	0.00	0.00	0.01	-0.00	000 * *
	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)
Δ_i Acres operated	0.00	-0.00	0.00*	-0.00	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δ_i Age	-0.03	-0.00	0.00	0.02	-0.02	-0.01*
	(0.02)	(0.00)	(0.00)	(0.02)	(0.04)	(0.01)
Δ_i Age squared	0.00	-0.00	-0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δ_i Soybean share	-0.24	0.01	0.01	-0.14	-1.06***	-0.06
	(0.19)	(0.01)	(0.02)	(0.18)	(0.36)	(0.05)
Δ_i Corn share	-0.39*	-0.02**	-0.04	-0.37*	-0.94**	0.17***
	(0.21)	(0.01)	(0.03)	(0.20)	(0.43)	(0.06)
Δ_i Wheat share	-0.28	0.03**	-0.01	-0.67***	-1.04**	-0.09
	(0.26)	(0.01)	(0.03)	(0.25)	(0.48)	(0.07)
Constant	0.44	-0.00	0.30	0.20	0.64	0.72**
	(1.02)	(0.02)	(0.34)	(0.55)	(2.31)	(0.29)
Year FE				YES		
County FE				YES		
Obs.	14,621	14,621	14,621	14,621	14,621	14,621
R^2	0.17	0.13	0.14	0.13	0.13	0.13

This table reports the full set of coefficients for the analysis in table A9 of the effects of insurance use on non-machinery investment and financing using an instrumental variable (IV) specification with first differences. Standard errors clustered by operation are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C11: **Full results: Insurance use and financial constraints**

	(1) Denied credit	(2) Deterred from credit use	(3) Any credit problem
Average insurance coverage	0.0005	0.0006	0.001
	(0.0009)	(0.0005)	(0.0009)
Share of acres insured	0.02	-0.002	0.02
	(0.02)	(0.01)	(0.02)
Risk tolerance	0.02***	-0.004**	0.01***
	(0.003)	(0.002)	(0.003)
Insured commodity: Corn	-0.07	0.07***	-0.01
	(0.06)	(0.02)	(0.06)
Insured commodity: Soybeans	-0.06	0.03*	-0.03
	(0.05)	(0.01)	(0.05)
Insured commodity: Wheat	-0.004	0.03*	0.02
	(0.06)	(0.02)	(0.06)
Insured commodity: Cotton	0.04	0.04*	0.08
	(0.06)	(0.02)	(0.06)
Insured commodity: Rice	-0.02	0.03	0.003
	(0.08)	(0.03)	(0.08)
Age	-0.005***	-0.0009***	-0.01***
	(0.0006)	(0.0003)	(0.0006)
Education: High school	-0.02	-0.01	-0.03*
	(0.02)	(0.01)	(0.02)
Education: College	-0.03*	-0.02**	-0.05***
	(0.02)	(0.01)	(0.02)
Total non-agricultural income ($)	-0.00***	0.00**	-0.00
	(0.00)	(0.00)	(0.00)
Male	0.003	0.01	0.02
	(0.07)	(0.03)	(0.07)
Non-white	-0.05	0.01	-0.04
	(0.06)	(0.04)	(0.07)
Spouse is co-operator	0.03*	0.01	0.03**
	(0.02)	(0.01)	(0.02)
Acres operated	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Soybean share	-0.01	0.003	-0.01
	(0.04)	(0.02)	(0.04)
Corn share	-0.01	-0.02	-0.03
	(0.04)	(0.02)	(0.04)
Wheat share	-0.13**	-0.001	-0.13**
	(0.06)	(0.03)	(0.06)
Revenues: $500,000 or more	0.04*	-0.01	0.03
	(0.02)	(0.01)	(0.02)
Revenues: Less than $250,000	-0.09***	0.01	-0.08***
	(0.02)	(0.01)	(0.02)
Primary output: Row crops	0.01	0.02	0.02
	(0.02)	(0.01)	(0.02)
Primary output: Specialty crops	0.03	0.02	0.05
	(0.04)	(0.02)	(0.04)
Constant	0.53***	0.51***	0.04
	(0.12)	(0.12)	(0.06)
State FE		YES	
Obs.	4,393	3,983	4,393
R^2	0.05	0.01	0.05

This table reports the full set of coefficients for the analysis in table A10 of an operator's self-reported credit constraints as a function of crop insurance use and risk tolerance. Robust standard errors appear in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.