rfcipDemand

# 📖 Introduction

rfcipDemand provides a reproducible pipeline for analyzing **U.S. Federal Crop Insurance Program (FCIP) demand**.

Its functionalities are grounded in the empirical strategies developed in:

* Tsiboe, F., & Turner, D. (2023). [**The crop insurance demand response to premium subsidies: Evidence from U.S. Agriculture**](https://doi.org/10.1016/j.foodpol.2023.102505) Food Policy, 119(3).
* Tsiboe, F., & Turner, D. (2023). [**Econometric identification of crop insurance participation**](https://doi.org/10.1017/age.2023.13) Agricultural and Resource Economics Review

Specifically, the package helps you:

* 🧩 Build county–crop–practice–plan–unit panels from **USDA RMA SOBTPU** and related sources
* 🔗 Merge **price and instrument variables**
* 🌾 Reconcile **acreage** using FSA and NASS data
* 📊 Estimate **FCIP demand systems** with fixed effects and two-way cluster-robust covariance
* ✅ Produce diagnostics, including robust first-stage strength

**Disclaimer:** This package uses USDA data but is not endorsed by or affiliated with USDA or the Federal Government.  
See <LICENSE> for terms.

# 📦 Installation

# Install from GitHub  
if (!requireNamespace("devtools", quietly = TRUE)) install.packages("devtools")  
devtools::install\_github("ftsiboe/rfcipDemand", force = TRUE, upgrade = "never")

# 🚀 Quick Start

The two most important functions are:

* fcip\_demand\_data\_dispatcher() → assemble the modeling data
* fcip\_demand\_sys\_estimate() → estimate demand equations
* adjust\_agent\_outcomes\_by\_elasticity() → adjust demand via estimated demand elasticities

## Example 1: Full sample estimation

In this example we would estimate a classic demand system for crop insurance with the aim of estimating demand responsiveness. That how much demand changes with each percentage change in premium rate. We would do this for the entire sample with consideration for hectrogeneity.

Model structure aligned to the approach in [Tsiboe & Turner (2023)](https://doi.org/10.1016/j.foodpol.2023.102505), updated with recent data.  
**NOTE:** Results may differ from the published articles due to RMA data revisions and pipeline improvements in this package.  
If you need *exact* replication of a paper, please use that study’s dedicated replication package (link to be added).

**Data**

# library(rfcipDemand)  
devtools::document()  
# 1) Identify fields for panel building  
FCIP\_INSURANCE\_POOL <- c("state\_code","county\_code","commodity\_code","type\_code","practice\_code")  
  
# 2) Build data (example years - keep short so examples are fast)  
df <- fcip\_demand\_data\_dispatcher(  
 study\_years = 2001:2024,  
 identifiers = c("commodity\_year", FCIP\_INSURANCE\_POOL, "insurance\_plan\_code", "unit\_structure\_code")  
)  
  
# Set price to 1 for crops with no RP/RP-HPE options [NEW]  
df[insurance\_plan\_code %in% c(1L, 90L), insurance\_plan\_code := 1L]  
df[insurance\_plan\_code %in% c(44L, 2L), insurance\_plan\_code := 2L]  
df[insurance\_plan\_code %in% c(25L, 42L, 3L), insurance\_plan\_code := 3L]  
df[, rp\_eligible := max(as.numeric(insurance\_plan\_code %in% 2:3)), by = "commodity\_code"]  
df[rp\_eligible == 0, price := 1]  
   
# 3) Prep variables   
data <- as.data.frame(df)  
data$net\_reporting\_level\_amount <- log(data$net\_reporting\_level\_amount/10000)  
data$coverage\_level\_percent\_aggregate <- log(data$coverage\_level\_percent\_aggregate)  
data$rate <- log(data$premium\_per\_liability\*(1-data$subsidy\_per\_premium))  
data$county\_acreage <- log(data$county\_acreage/10000)  
data$rent <- log(data$rent/1000)  
data$price <- log(data$price)  
data$tauS0 <- log(data$tau\*(1-((data$subsidy\_rate\_65+data$subsidy\_rate\_75)/2)))  
data$trend <- data$commodity\_year - min(data$commodity\_year, na.rm=TRUE)  
  
for(i in unique(data$commodity\_code)){ data[,paste0("Crop\_",i)] <- ifelse(data$commodity\_code %in% i,1,0)\*data$trend }  
for(i in unique(data$commodity\_year)){ data[,paste0("year\_",i)] <- ifelse(data$commodity\_year %in% i,1,0) }  
data <- data[names(data)[!names(data) %in% c(paste0("year\_",max(data$commodity\_year,na.rm=T)),"Crop\_41")]]

**🧮 Estimate the model**

# 4) Specify the system  
  
model <- list(  
 name = "demo\_sys",  
 FE = TRUE,  
 outcome = c("net\_reporting\_level\_amount","coverage\_level\_percent\_aggregate"),  
 endogenous = "rate",  
 excluded = "tauS0",  
 partial = c("trend",names(data)[grepl("Crop\_",names(data))],names(data)[grepl("year\_",names(data))]),  
 disag = NULL,  
 included = c("county\_acreage","price","rent")  
)  
  
# 5) Estimate demand system  
res <- fcip\_demand\_sys\_estimate(model = model, data = data)  
  
write.csv(res,"data-raw/examples/example1.csv")

**📊 Discussion of Results**

The outputs (see Table 1 below) from fcip\_demand\_sys\_estimate() are structured objects that typically include:

* **System coefficients**: Estimated elasticities of demand with respect to premium rates, coverage levels, and control variables.
* **Robust inference**: Standard errors clustered by county and year, consistent with best practices in applied demand modeling.
* **First-stage diagnostics**: Strength of excluded instruments (e.g., tau), ensuring valid identification of the endogenous premium rate.
* **Equation-level summaries**: For multi-equation systems, results are returned per outcome (e.g., insured acreage (Gamma) and coverage level (Theta1)).

**Table 1: Crop Insurance Demand System for US Federal Crop Insurance Pools (2001/24)**

devtools::document()  
#> ℹ Updating rfcipDemand documentation  
#> ℹ Loading rfcipDemand  
library(knitr)  
example1 <- readr::read\_csv("data-raw/examples/example1.csv", show\_col\_types = FALSE)  
#> New names:  
#> • `` -> `...1`  
  
# Variable name mapping  
var\_labels <- c(  
 "(Intercept)" = "(Intercept)",  
 "tilda\_rate" = "Paid premium rate",  
 "tilda\_county\_acreage" = "County planted acres",  
 "tilda\_price" = "Expected crop price",  
 "tilda\_rent" = "State rental rate for land",  
 "residCov\_11" = "σ\_aa",  
 "residCov\_22" = "σ\_θθ",  
 "residCov\_12" = "σ\_θa",  
 "N" = "Number of observations",  
 "NFE" = "Number of insurance pools",  
 "JTest" = "J-test",  
 "FTest" = "Weak-instrument: F-statistics"  
)  
  
final\_tbl <- format\_fcip\_demand\_table(example1, var\_labels)  
  
# Print table  
kable(final\_tbl,  
 col.names = c("Variables","Estimates"),  
 format = "pipe", # <- ensures compatibility with GitHub markdown  
 align = c("l","c"))

| Variables | Estimates |
| --- | --- |
| Coverage level |  |
| (Intercept) | 0.000 (0.003) |
| Paid premium rate | -0.036\*\*\* (0.014) |
| County planted acres | -0.002 (0.002) |
| Expected crop price | -0.011 (0.019) |
| State rental rate for land | -0.000 (0.072) |
| Insured acres |  |
| (Intercept) | 0.000 (0.048) |
| Paid premium rate | -0.167 (0.115) |
| County planted acres | 0.311\*\*\* (0.053) |
| Expected crop price | 0.377 (0.340) |
| State rental rate for land | -0.053 (0.593) |
| Total protection response |  |
| Paid premium rate | -0.197\* (0.117) |
| County planted acres | 0.308\*\*\* (0.054) |
| Expected crop price | 0.361 (0.350) |
| State rental rate for land | -0.054 (0.652) |
| Covariance matrix |  |
| σ\_aa | 3.862 |
| σ\_θθ | 0.015 |
| σ\_θa | 0.046 |
| Additional statistics |  |
| Number of observations | 1013922.000 |
| Number of insurance pools | 151393.000 |
| J-test | 0.000 |
| Weak-instrument: F-statistics | 884.241 |

example1$Estimate <- round(example1$Estimate,3)  
rownames(example1) <- paste0(example1$demand,"\_",example1$coef)

**Notes:** Crop insurance demand is modeled via a multi-equation structural model of crop insurance demand at the intensive and extensive margins measured by coverage level and insured acres. An insurance pool is defined as the unique combinations of crops, county, insurance unit, insurance plan, irrigation practice, and organic practice. The data used was constructed by the authors using primary data from (1) Risk Management Agency, (2) Farm Service Agency’s crop acreage data, and (3) NASS Quick Stats.

Significance levels – *p<0.1,* ***p<0.05,*** p<0.01. Standard errors in parentheses are clustered by insurance pool and year.

The results highlight distinct responses across the intensive and extensive margins of crop insurance demand. At the intensive margin (coverage level), the producer-paid premium rate enters with the expected negative sign (-0.036), implying that a 1% increase in the premium rate is associated with a -0.036% decrease in chosen coverage levels. However, the effect is statistically insignificant, reflecting the limited responsiveness of coverage choices to cost signals. Other covariates, including county planted acres, crop price, and rental rates, are similarly imprecise and not distinguishable from zero.

At the extensive margin (insured acres), scale effects dominate. County planted acres exhibit a positive and statistically significant coefficient (0.311), meaning that a 1% increase in planting area raises insured acreage by about 0.311%. The premium rate again shows a negative effect (-0.167), suggesting a 1% increase in rates reduces insured acreage by nearly -0.167%, though the standard error is large and the estimate is not significant.

For the total protection response, county planted acres remain a key driver (0.308), indicating that scale continues to push overall demand upward by roughly 0.308% for each 1% increase in planted acres. The premium rate reduces total protection (-0.197), implying that a 1% increase in paid premiums reduces total protection demand by about -0.197%, though again, the estimate is not statistically precise.

The covariance matrix provides additional insight. The positive cross-covariance (σ\_θa = 0.046) indicates that unobserved factors increasing demand for coverage level also raise demand for insured acres, and vice versa. However, the relationship is asymmetric: the variance of insured acres (σ\_aa = 3.862) dwarfs that of coverage level (σ\_θθ = 3.862), suggesting that shocks to acreage drive most of the variation in joint demand.

Overall, these estimates point to farm size (planted acres) as the most consistent determinant of insurance demand, while the dampened and imprecisely estimated response to premium rates underscores how subsidies mute price sensitivity. The positive covariance between margins further suggests complementarities in demand, but the dominant source of variation lies in the extensive margin, highlighting the central role of scale in shaping crop insurance participation.

## Example 2: Sub sample estimation

In this example we would consider example but under the case where one is interested in heterogeneity in demand response.

For this example we will consider heterogeneity by commodity and state.

The model structure and data are the same as example 1.

**🧮 Estimate the model**

# 4) Specify the system  
  
model <- list(  
 name = "demo\_sys",  
 FE = TRUE,  
 outcome = c("net\_reporting\_level\_amount","coverage\_level\_percent\_aggregate"),  
 endogenous = "rate",  
 excluded = "tauS0",  
 partial = c("trend",names(data)[grepl("Crop\_",names(data))],names(data)[grepl("year\_",names(data))]),  
 disag = NULL,  
 included = c("county\_acreage","price","rent")  
)  
  
# 5) Estimate demand system  
res <- fcip\_demand\_sys\_estimate(model = model, data = data)  
  
write.csv(res,"data-raw/examples/example1.csv")

# 📚 Citation

If you use rfcipDemand in your research, please cite:

* Tsiboe, F., & Turner, D. (2023). [**The crop insurance demand response to premium subsidies: Evidence from U.S. Agriculture**](https://doi.org/10.1016/j.foodpol.2023.102505) Food Policy, 119(3).
* Tsiboe, F., & Turner, D. (2023). [**Econometric identification of crop insurance participation**](https://doi.org/10.1017/age.2023.13) Agricultural and Resource Economics Review

# 🤝 Contributing

Contributions, issues, and feature requests are welcome. Please see the [Code of Conduct](code_of_conduct.md).

# 📬 Contact

Questions or collaboration ideas?  
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Star the repo ⭐ if you find it useful!