Volatility and Under-Insurance in Economies with Limited Pledgeability: Evidence from a Frost Shock

Victor Orestes (Wharton)
Thiago Silva (BCB)
Henry Zhang (CUHK)

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Motivation

- Under-insurance is prevalent in many settings with financially constrained households and small firms, even when premiums are subsidized
  - e.g. health, home, flood, wildfire, **crop**
- Many papers have sought behavioral explanations, but we show that financial frictions can partially explain under-insurance with repeated net worth shocks
- What are the general equilibrium consequences of under-insurance?
  - Production network, *financial markets*, and insurance markets?

Research Question

In response to an unexpected net worth shock, commonly seen in environmental settings, how does the interaction of insurance and financial constraints affect firms' subsequent demand for hedging and investment?

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Our Contribution

- Model: Firms' limited commitment and pledgeability constraint generate differential responses to shock magnitude by insurance status
- Empirics: Lasting differential responses from a one-time shock. Uninsured have, for each pct pt damage in capital stock:
  - 1.5 pct pts less outstanding debt
  - 0.2 months longer maturity
  - 0.6 pct pts lower investment
- Policy implication: Neither insurance subsidies nor emergency credit lines addresses these differential outcomes as effectively as directly loosening the [state-contingent] borrowing constraint

Comparison to the Literature

Causes and consequences of under-insurance: Caballero and Krishnamurthy 2003, Dávila and Korinek 2018, Rampini and Viswanathan 2022, etc.

- **Our model predicts that limited pledgeability of collateral results in coffee farmers with low net worth neither saving to use internal funds nor hedging against negative shocks, with GE consequences on the coffee price and distribution of farmer wealth.**

Credit and insurance: Cole and Xiong 2017; Casaburi and Willis 2018; McIntosh, Sarris, and Papadopoulos 2013; Annan 2022; Lane 2024, etc.

- **We show that credit and insurance behave as complements, from pledgeability constraints that bind after a shock rather than ex ante.**

Financial transmission of weather shocks: Bergman, Iyer, and Thakor 2020; Brown, Gustafson, and Ivanov 2021; Cortés and Strahan 2017, etc.

- **Our setting and mechanism differ from each of these papers: the physical shock, causing a reduction in the capital stock, interacted with insurance is what generates our financial and hedging results. We also have detailed payment and credit data for a granular exploration.**

Theory - Overview

Currently in the Draft: Partial Equilibrium

- Risk-averse firms are subject to shocks to their capital stock
- Firms can write contracts with risk-neutral financial intermediaries conditioning on state (shock) realization under limited pledgeability
- **Endogenously Incomplete Markets**: Equivalence between
  - the constrained optimal contract maximizing farmers' utility
  - a market featuring one-period state-contingent savings (insurance) and non-state-contingent debt contracts, all with collateral constraints

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Today: Preliminary Discussion of General Equilibrium with Endogenous Coffee Price

- Debt limit depends on the coffee price, determined by the aggregate state, as well as the idiosyncratic state
- Work-In-Progress: Estimation with SMM using the empirical results.

Setup

Risk averse farmers, maximizing stochastic utility with a finite set of states s_t:

$$U_t^E(\{c_t\}) = \mathbb{E}\left[\sum_{k=0}^{\infty} \beta^k u(c_t)\right],$$

Farmer produces a common good with common technology

$$y_t = Ak_t^{\alpha},$$

Capital stock is subject to shocks θ, also captures discounting

$$k(s_t) = \theta(s_t)\left(i_{t-1} + k_{t-1}\right),$$

Limited Commitment: Farmers can default and run away with a fraction $(1-\lambda)$ of $p_t y_t$

Non-Exclusion: Farmers cannot be excluded from the credit market

Sequence $\{c(s^t), t(s^t), k(s^t)\}_{t\geq\tau}$ to maximize

$$\underbrace{U\left(\{c(s^t)\} \mid s^\tau\right)}_{\text{Continuation Utility}} := E_\tau\left[\sum_{t=\tau}^{\infty}\beta^{(t-\tau)}u\left(c_t\right)\right],$$

subject to the current and future period budget constraints, $\quad \forall t \geq \tau$:

$$\underbrace{\tilde{p}(s^t)k\left(s^{t-1}\right)^\alpha + \theta(s^t)k^*\left(s^{t-1}\right) - t\left(s^\tau\right)}_{\text{Net Worth, } W(s^t)} \geq c\left(s^t\right) + k(s^t),$$

Lender participation constraint:

$$\underbrace{E_\tau\left[\sum_{t=\tau}^{\infty}R^{-(t-\tau)}t_t\right] \geq 0}_{\text{Non-Negative Net Present Value}} \quad .$$

Farmer's incentive constraint, for all s^t, $\{\hat{c}(s^t)\}$ solving the optimal contract in case of default:

$$\underbrace{U\left(\{c(s^t)\} \mid s^t\right)}_{\text{Continuation Utility}} \geq \underbrace{U\left(\{\hat{c}(s^t)\} \mid s^t\right)}_{\text{Continuation Utility after Default}} \quad .$$

Endogenously Incomplete Markets

Proposition: A consumption allocation is the outcome of the optimal contract if and only if the allocation is the outcome of an economy where farmers only have access to a sequence of one-period state-contingent savings contracts $\{h(s^t)\}_{t \geq \tau}$ and one period non-state-contingent debt contracts $\{d_t\}_{t \geq \tau}$:

$$\underbrace{d_t}_{\text{Debt}} \leq \underbrace{\lambda p(s^t)\theta(s_t)^{\alpha} k(s^t)^{\alpha}}_{\text{Pledgeability constraint}} + \underbrace{h(s^t)}_{\text{Insurance}}, \qquad \text{for all}$$

$$d_t \geq 0, \quad h(s^t) \geq 0, \qquad \text{for all } s^t,$$

Intuition

1. Borrowing more than what is pledgeable requires insurance.
2. But insurance premium needs to be paid **up front**.
3. **Implication:** access to credit and insurance are not *substitutes*.

Market Clearing

Price determination: Price of coffee is given by

$$p(s^t) = Y(s^t)^{-\frac{1}{\gamma}},$$

where $\gamma > 0$ is constant and $Y(s^t)$ is the aggregate supply, given by:

$$Y(s^t) = \int_0^1 y_i(s_i^t) di$$

we set $\gamma = 0.4$ (inelastic demand). Interest rate $R > 1$ is exogenous and constant.

Numerical Exercise to Motivate the Event Study

- Continuum mass 1 of farmers.
- Farmers' idiosyncratic shock values are $\theta = 0.3$ (bad) or $\theta = 0.95$ (good).
- We consider 2 aggregate states:
  1. Good state: 20% of the farmers receive the shock
  2. Bad state: 50% of the farmers receive the shock
- Set $\alpha = 0.3$, $\lambda = 0.7$, $\beta = 0.9$, and $R = 1.05$
- $u(c) = c_t^{1-\sigma}/(1-\sigma)$, $\sigma = 2$.
- Transition probabilities set such that the unconditional distribution of good and bad states is:
$$P_S = [0.8;\ 0.2].$$
- **Solution:** Global solution combining a Krusell-Smith method with an endogenous grid method.

Numerical Solution

- Perceived Law of Motion (PLM): Given a set of moments m_t (e.g. aggregate capital) of the distribution of Ak_{it}^{α}, farmers predict:

$$Y_{t+1}(S_{t+1}) = \int_0^1 A_i \theta(s_{it+1})^{\alpha} k_{it+1}^{\alpha} di = f(m, S_t, a),$$

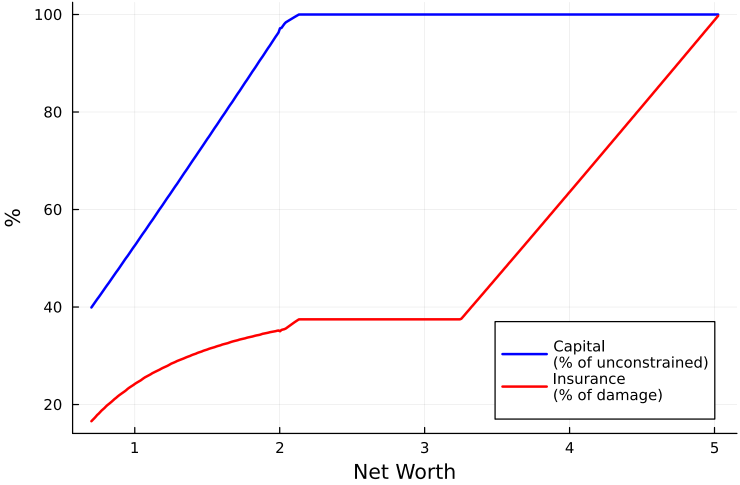
  where $f(\cdot)$ is a known functional form, and a is a finite-dimensional parameter vector.

- Start with initial guess a_0:
  1. Solve household problem for given a.
  2. Simulate economy, generate $\{m_t, S_t, Y_{t+1}\}$.
  3. Re-estimate a from simulated data.

- Repeat until change in a (or prediction error) is below tolerance

Additional Details

Model Implication: Insurance Increases with Net Worth



Model-Derived Event Study Setup

- We simulate the economy for 11 thousand periods (10 thousand farmers), discarding the first thousand periods of the simulation.
- We define $\mathrm{Shock}_{it} = 1$ if the aggregate state is bad in period t and farmer i received the shock.

Model-Derived Event Study Setup

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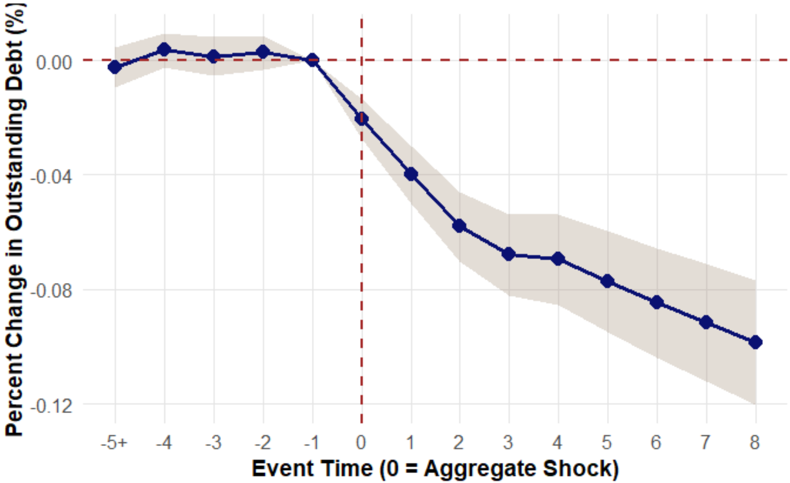
- We define $\mathrm{Shock}_{it} = 1$ if the aggregate state is bad in period t and farmer i received the shock.

$$y_{it} = \sum_{\tau=-G}^{M} \beta_{\tau}^{\mathrm{NI}} \mathrm{Shock}_{i\tau} + +\alpha_i + \alpha_t + \epsilon_{it}.$$

- $\mathrm{Shock}_{i\tau}$ indicator if the farm received the shock in a bad state of the world at τ.
- i is farmer, t is quarter.
- y_{it} is the outcome of interest.
- Farmers are uninsured.

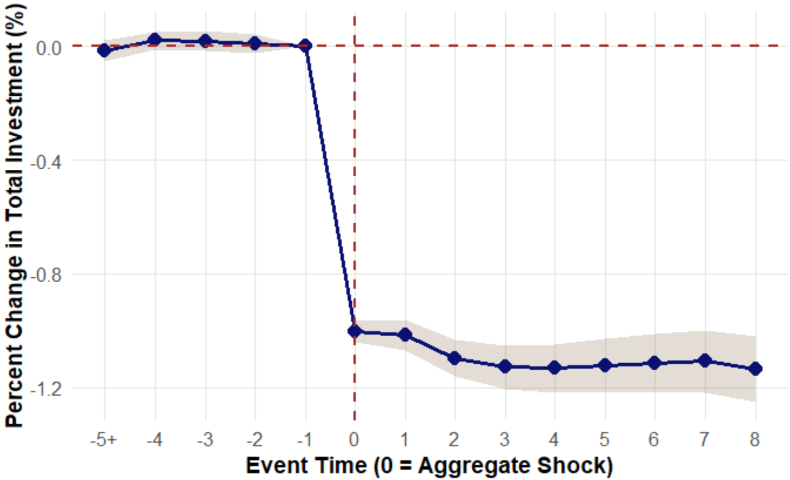
Model-Implied Debt Load Responses

Cumulative effects of $\beta_{\tau}^{\mathrm{NI}}$

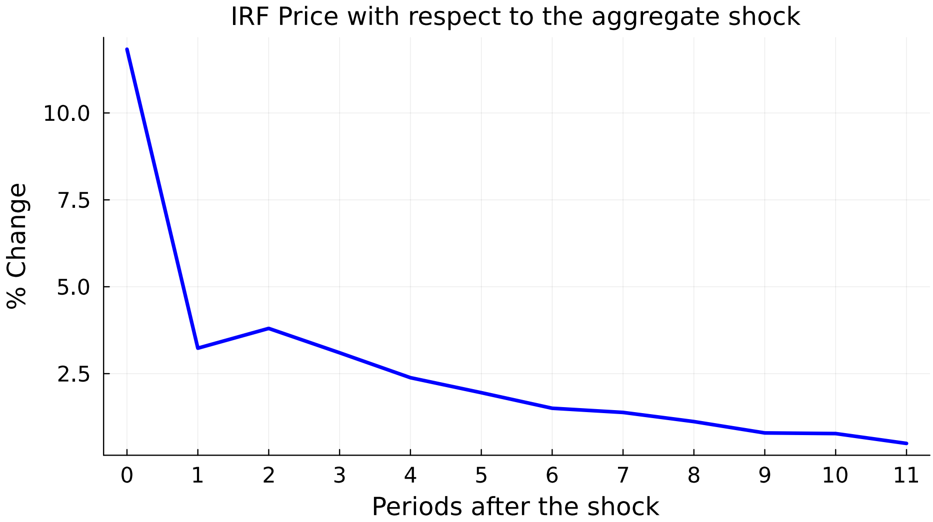


Model-Implied Investment Responses

Cumulative effects of β_τ^{NI}



Endogenously Persistent Impact through the Coffee Price



Empirical Setting: Frost Shock in Brazil

- In July 2021, four frost waves struck agricultural regions in Brazil, with heterogeneous impact across crops and plots
- As Brazil accounts for almost 40% of the world's production, prices soared in 2021 and remained high during 2022.

Climate Capital Agricultural commodities + Add to myFT

Weather shocks in Brazil ripple across global commodities markets

FT

Coffee Prices Jump to Six-Year High as Brazilian Frost Threatens Crop

Arabica-bean prices have leapt almost a third in July in latest instance of extreme weather sending jitters through commodity markets

WSJ

Price Time Series | Futures Prices | Futures Volume | Map of Coffee Production

Empirical Setting: Coffee in Brazil

Coffee plants are perennial, so the frost negatively affected farmers' net worth

Coffee Price Time Series | Map of Coffee Production

Datasets

All accessed through the Central Bank of Brazil:

- Publicly subsidized **rural credit and insurance** (PROAGRO) at the contract level.
- **Private agricultural insurance** at the contract level.
  - Also, OTC data at the contract level, with information about FX hedging and coffee future contracts.
- **Credit registry** (SCR) at the loan level.
  - We also use the **Rural Credit Registry** (SICOR), which also contains information about the farmer's activity (which crops the farm grows), farm area, partial data on expected and realized production, and geographic location of the farms.
- **Electronic payments** at the transaction level, with information about each counterparty's municipality and 7-digit CNAE sector (roughly the same as a 6-digit HS code)

Measurement | Summary Stats

Credit Regression Specification

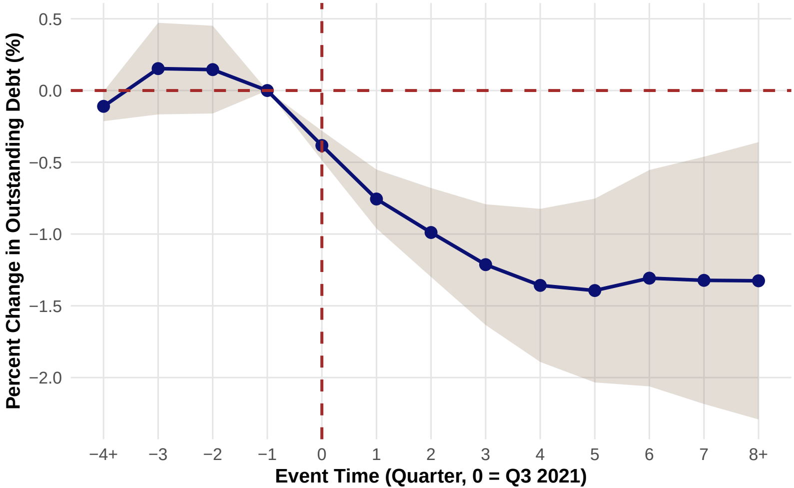
We use the following specification for the credit event study (quarterly frequency).

$$y_{ijt} = \sum_{\tau=2020Q1}^{2023Q4} \beta_\tau^{\mathrm{I}} \mathrm{fs}_{ij\tau} \mathrm{Ins}_{ij} + \sum_{\tau=2020Q1}^{2023Q4} \beta_\tau^{\mathrm{NI}} \mathrm{fs}_{ij\tau} \mathrm{No\_Ins}_{ij} + \alpha_{ij} + \alpha_{jgt} + \epsilon_{ijt}.$$

- i is farmer, j is municipality, t is quarter, g is insured vs uninsured
- y_{ijt} is (log) of outstanding debt.
- Ins is an indicator of insured at the time of the shock
- **Intuition:** comparing credit issuance to affected vs unaffected farmers, after accounting for farmer fixed effects and municipality-time shocks

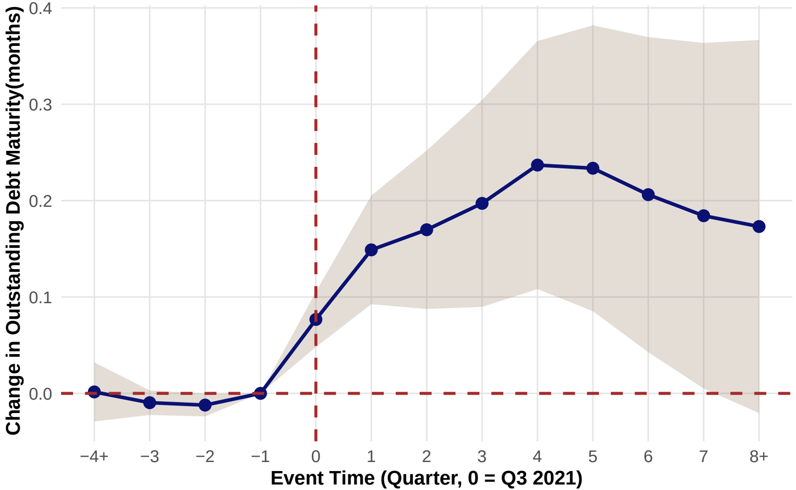
Non-Insured Farmers' Debt Load | Non-Insured Farmers' Debt Maturity | Insured Farmers' Debt Load | Insured Farmers' Debt Maturity

Non-Insured Farmers' Debt Load ($\hat{\beta}_{\tau}^{\mathrm{NI}}$ Cumulative Effects)



Comparison with Insured
Regression

Non-Insured Farmers' Debt Maturity ($\hat{\beta}_{\tau}^{\mathrm{NI}}$ Cumulative Effects)



Comparison with Insured

Regression

Payment Regression Specification

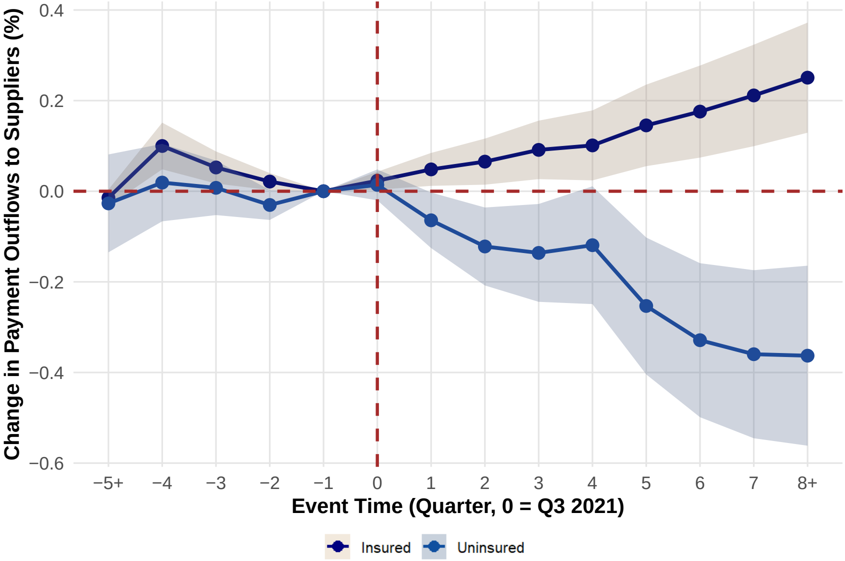
We use the following specification to proxy for investment using payments data aggregated quarterly:

$$y_{ijst} = \sum_{\tau=2020\text{Q1}}^{2023\text{Q4}} \beta_{\tau}^{\text{I}} \text{fs}_{ij\tau} \text{Ins}_i + \sum_{\tau=2020\text{Q1}}^{2023\text{Q4}} \beta_{\tau}^{\text{NI}} \text{fs}_{ij\tau} \text{No\_Ins}_i + \alpha_{ijs} + \alpha_{jmt} + \epsilon_{ijt}.$$

- i is farmer, j is municipality, s is the supplier, t is quarter, m is the supplier 7-digit CNAE code (similar to 6-digit HS code).
- y_{ijst} is payment *outflows* to suppliers of agricultural inputs (seeds, fertilizers, capital replenishment).
- $\text{Ins}, \text{No\_Ins}$: indicator of insured vs non-insured in 2021.
- **Intuition:** comparing within the same municipality payment outflows to a given sector from affected vs unaffected farmers (after accounting for customer x supplier fixed effects).

Skip to Conclusion

Insured $\hat{\beta}^{\mathrm{I}}_{\tau}$ Invested More, Non-Insured $\hat{\beta}^{\mathrm{NI}}_{\tau}$ Invested Less



Additional Results

- Insurance take-up and intensive margin both decrease for affected uninsured coffee (perennial) farmers, but increased for unaffected coffee farmers and unchanged for annual crop farmers
- No significant effects on the interest rate nor *default rate*.
- Margin of adjustment was debt renegotiation, extending the maturity of existing debt.
- No significant effects on insured farmers' debt composition.

Insurance Results | Default Results | Interest Rate Results | Skip to Conclusion

Implication: Emergency Credit Lines

- Emergency credit lines *intermediated* by the financial sector **may not be effective** when the intermediaries are unconstrained
- Corroborated in the data: the majority of what was allocated for emergency credit lines was not lent, and was lent disproportionally more to insured farmers.
  - Empirically, this pattern was also observed in the Covid-19 emergency credit lines in the US (Joaquim and Wang 2022).
- **Conclusion:** Emergency credit lines do not substitute for insurance when the same underlying friction limits both insurance and credit take-up.

Implication: Increase the Effective Pledgeability of Collateral

CPR (crop-settled) and CPR-F (money-settled) futures:

- Lenders can use satellite imagery to verify farmers' crop conditions and real-time harvest status
- By credibly pledging future harvest to lenders, farmers can increase borrowing capacity given a fixed amount of assets as collateral

Fractionalization from tokenization of land:

- Comprehensive registry of land + tokenization could allow farmers to pledge the unused value of land as collateral to other lenders, increasing competition between lenders in financing terms

Conclusion

- We show evidence on the impact of Brazil's frost shock on payments to other firms, credit, and insurance
  - Insurance take-up decreased for affected farmers.
  - Uninsured farmers who are affected borrowed less than the unaffected ones.
  - Uninsured farmers decreased expenditure on intermediate good, unlike their insured counterparts.
- We discussed how this is consistent with a model where limited pledgeability negatively impacts farmers' ability to insure themselves against shocks.
- Next steps:
  - SMM to quantify the determinants of under-insurance and policy counterfactuals
  - Heterogeneity regressions in the payments data

Appendix

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Rampini, Adriano and S. Viswanathan (2022). "Financing Insurance". In: *Working Paper*.

Household Problem Solution via Endogenous Grid Method (EGM)

- For each aggregate price P and agent type a:
  1. Construct $\tilde{\theta}_{j,s}$ from PLM parameters and current P.
  2. Initialize V_w with marginal utility guesses.
  3. Consider cases on a fine wealth grid:
     - **Unconstrained:** Invert Euler equation to find c and w' for each future state.
     - **Partially constrained:** Some future-state borrowing limits bind.
     - **Fully constrained:** All future-state borrowing limits bind.
  4. Iterate until V_w converges; store policies $k(w,s)$, $w'(w,s,s')$, $c(w,s)$.
  5. Wrap policies into interpolation objects indexed by P.

Return to Numerical Solution Summary

Krusell-Smith Simulation and PLM Update

- **Simulation:**
  1. Simulate T periods with N agents (insured & uninsured) under given PLM.
  2. Aggregate capital and compute price from production function and shock structure.
  3. Use precomputed policy interpolants to evolve individual (w, s).
- **PLM update:**
  1. Regress $\log P_{t+1}$ on current-state dummies, interactions with $\log P_t$, and next-state dummies.
  2. Map coefficients to new PLM parameters.
  3. Repeat outer loop until mean-squared change in parameters is small.

Return to Numerical Solution Summary

Differences from Standard Krusell-Smith

- **Heterogeneous collateral constraints:** Borrowing limits depend on future-state productivity $\tilde{\theta}$ and differ across insured and uninsured agents.
- **Four-state individual process:** Combines aggregate state (good/bad) with individual damage (good/bad) $\Rightarrow$ 4 discrete states instead of 2.
- **Two agent groups:** Solve policy functions separately for insured and uninsured households, with different (λ, β).
- **Price determination:** Output price P_t from CES demand with elasticity 0.4^{-1}, rather than Cobb–Douglas rental rate.
- **EGM with multiple constraint regimes:** Explicitly handles unconstrained, partially constrained, and fully constrained cases in value function iteration.
- **PLM functional form:** Regression includes next-period state dummies S_{t+1} in addition to current S_t and $\log P_t$.

Return to Numerical Solution Summary

Insurance and Hedging among Coffee Farmers

- Our sample consists of all coffee farms that ever borrowed using rural credit lines in the period of 2020-2023.
  - 100,848 farms; the majority of farmers only own one farm
- Lack of insurance is prevalent among coffee farms in our sample.
  In 2021:
  - 20% had quantity-based insurance.
  - 0.28% had FX hedging.
  - 0.13% entered in price hedging in local markets.
- Insured farms
  - are larger (103 vs 59 acres).
  - and borrow at cheaper rates (5.6% vs 9.5% annually)
  - related to an insurance premium
- Around 27% were hit by the frost shock.

Datasets

Measuring the Frost Shock using Insurance Claims Data

- We observe contract-level insurance claims, identified at the coffee farm level (longitude and latitude coordinates).
- Insurance claims include information on the total amount paid and the most prevalent event (e.g., frost, drought, etc).
  - Insurance claims are only paid after an agronomist validates the extent of the damages.
- Farm-level frost shock measure constructed from insurance claims data using a regularized spatial interpolation
  - Perhaps less measurement error of the shock impulse than the typical method of using weather data, because small differences in elevation, soil, and temperature seem to correspond to large differences in claims

Datasets

Frost Shock Measurement

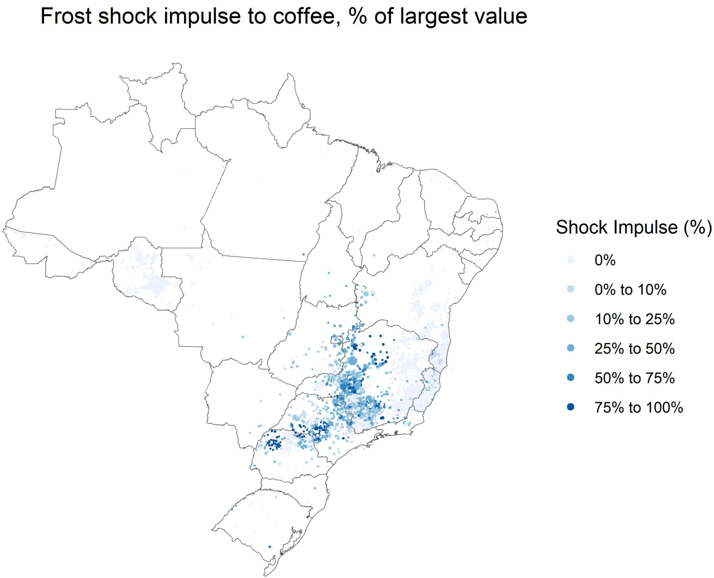
- For a given insured coffee farmer i we observe:
  - x_i: Farm coordinates.
  - Our frost shock measure fs_i: the ratio of frost damage insurance claims to total insured value.
- For an uninsured farmer j we compute the frost shock measure fs_j via a regularized spatial interpolation:

$$\mathrm{fs}_j = \frac{\sum_{i \in \mathcal{N}_j} w_i(x_j)\mathrm{fs}_i}{\sum_{i \in \mathcal{N}_j} w_i(x_j)}, \quad \text{weights } w_i(x_j) = \frac{1}{d(x_i, x_j)^\beta},$$

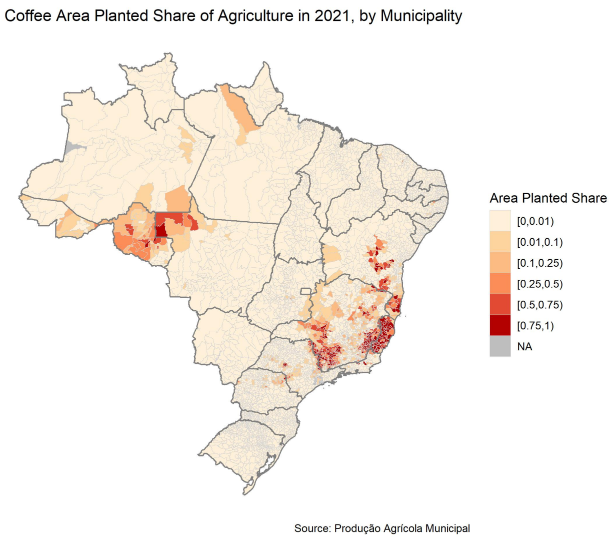
  where $d(x_i, x_j)$ is the distance between farms, and $\mathcal{N}_j$ is the set of j $k-$nearest neighbors.
- Both β and k are chosen by cross-validation.

CDF of frost shock for insured vs uninsured

Frost Shock Measurement



Coffee Planting Share



Return to Setting | Map of Frost Shock Impulse

Frost shock measure: insurance claims vs weather

Left-hand-side is the ratio of total claims to insured value for farmer f growing crop c with insurer i in municipality j in year t. The right-hand-side is the frost shock defined as the crop-specific claims to insured value for crop year 2021.

$$\left(\frac{\text{Claims}}{\text{Insured Value}}\right)_{fijt} = \sum_{\tau=2017}^{2021} \beta_\tau \text{fs}_{fcij} + \alpha_f + \alpha_{cijt} + \epsilon_{fcijt}.$$

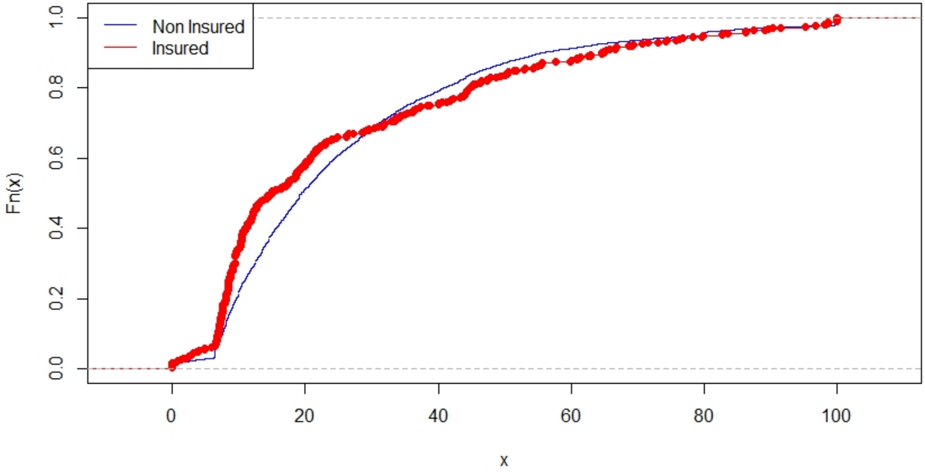
Sanity Check: Close to 1-for-1 Impact on Insurance Claims for Frost

Table: Regressions of Total Claim-to-Insurance on Frost Claim-to-Insurance

Coffee shock 2021	0.87	0.76	0.76
	[17.2]	[30.4]	[29.7]
Corn shock 2021	0.56	0.61	0.55
	[42.6]	[80.5]	[69.5]
Wheat shock 2021	0.76	0.77	0.75
	[76.6]	[102.6]	[93.5]
Farmer FE	X	X	X
Crop x Year FE	X	X	
Crop x Year x Insurer FE			X
Farm area control	X	X	X
Expected output control	X		
Observations	1,197,291	1,617,602	1,598,056

Return

Frost Shock Measure: Insured vs Non-Insured



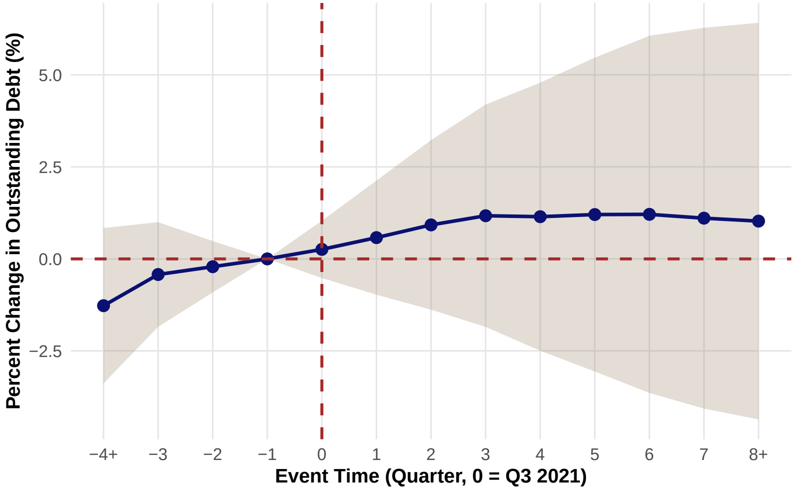
Robustness Check: Net Worth Shock

Table: Regressions of Pct Damage on Lagged Net Worth Shock and Shock Indicators

Lag Net Worth Shock	-43.2		
	[-47]		
Lag Shock Indicator 1		-1728.8	
		[-56]	
Lag Shock Indicator 2			-103.5
			[-5.3]
Lag Shock Indicator 3			-1664.4
			[-47.3]
Farmer x Crop FE	X	X	X
Crop x Year FE	X	X	X
Observations	750,348	750,348	750,348

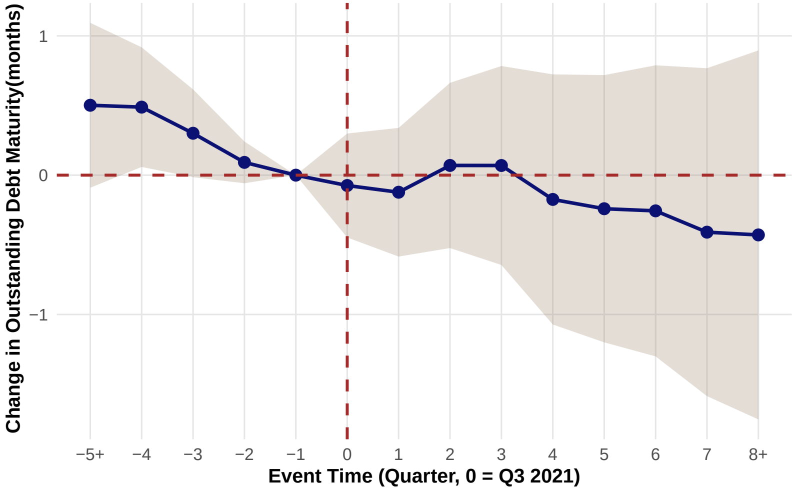
Return

Insured Farmers' Debt Load ($\hat{\beta}^{\mathrm{I}}_{\tau}$ Cumulative Effects)



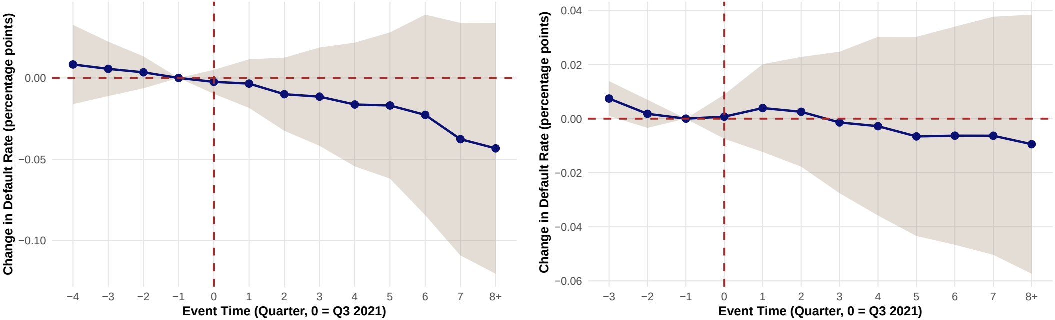
Comparison with Non-Insured | Regression

Insured Farmers' Debt Maturity ($\hat{\beta}^{\mathrm{I}}_{\tau}$ Cumulative Effects)



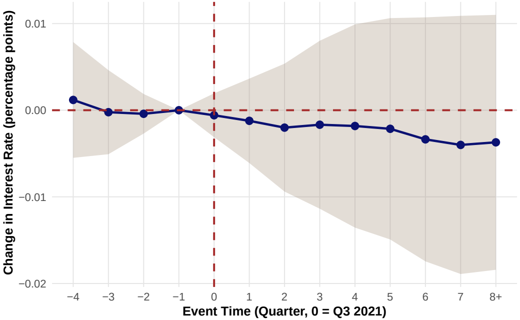
Comparison with Non-Insured | Regression

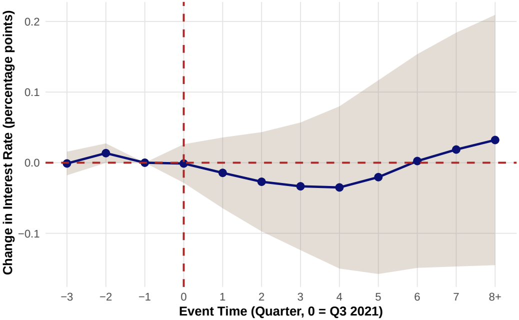
Default ($\hat{\beta}_{\tau}^{\mathrm{I}}$ on left, $\hat{\beta}_{\tau}^{\mathrm{NI}}$ on right)



Return to Additional Results

Interest Rate ($\hat{\beta}^{\mathrm{I}}_{\tau}$ on left, $\hat{\beta}^{\mathrm{NI}}_{\tau}$ on right)

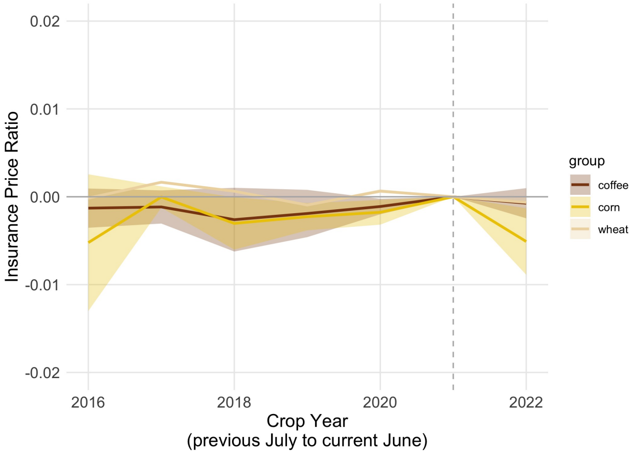




Return to Additional Results

Impact on Insurance Prices

$$\left(\frac{\text{Premium}}{\text{Insured Value}}\right)_{fcijt} = \sum_{\tau=2017}^{2022} \beta_\tau \mathrm{dh}_j + \alpha_f + \alpha_{cijt} + \epsilon_{fcijt}.$$



Return

Impact on Insurance Prices

Table: Regressions of $\frac{\text{Premium}}{\text{Insured Value}}$

Coffee shock 2021	0	-0.001	-0.003
	[0.4]	[-0.8]	[-1.8]
Corn shock 2021	-0.007	-0.005	0.006
	[-11.8]	[-2.6]	[5.9]
Wheat shock 2021	-0.001	-0.001	0.002
	[-0.9]	[-2.2]	[1.1]
Farmer FE	X	X	X
Crop x Year FE	X	X	
Crop x Year x Insurer FE			X
Farm area control	X	X	X
Expected output control	X		
Observations	1,840,382	2,336,587	2,362,363

Return

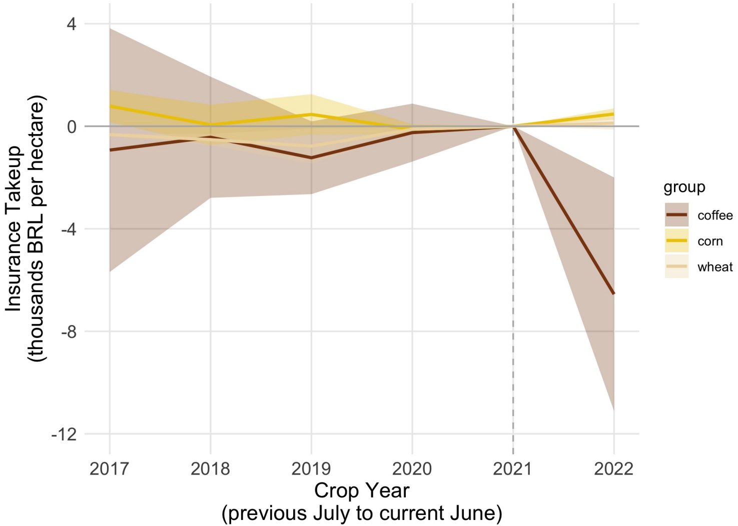
Insurance Regression Specification

$$y_{ijct} = \sum_{\tau=2017}^{2022} \beta_\tau \mathrm{fs}_{ijc\tau} \mathrm{Ins}_{ijc} + \alpha_{ijc} + \alpha_{jct} + \epsilon_{ijct}.$$

- i is farmer, j is municipality, c is crop, t is year (growing season)
- Ins_{ijc} is an indicator for insured at the time of the shock
- y_{ijct} is the response variable of interest: $\frac{\text{Insured Value (BRL)}}{\text{Area (Hectares)}}$.
- **Intuition:** comparing within the same municipality, insurance take-up of affected farmers versus unaffected farmers (after accounting for individual fixed effects).

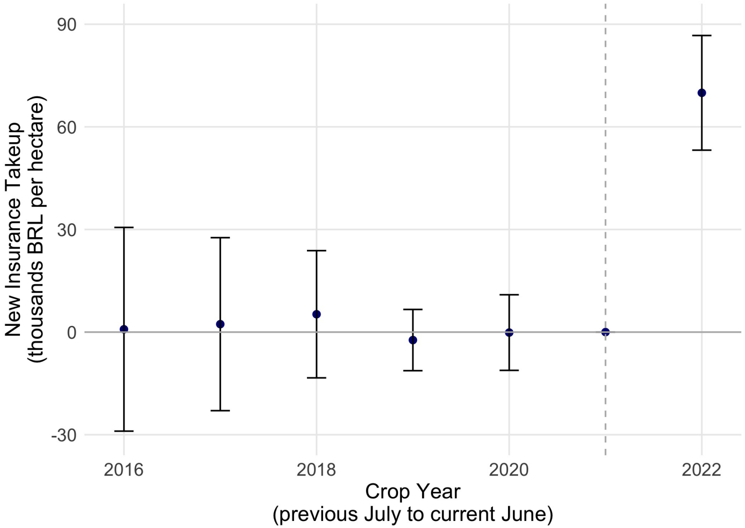
Return to Additional Results

Affected Farmers Take up Less Quantity-Based Insurance

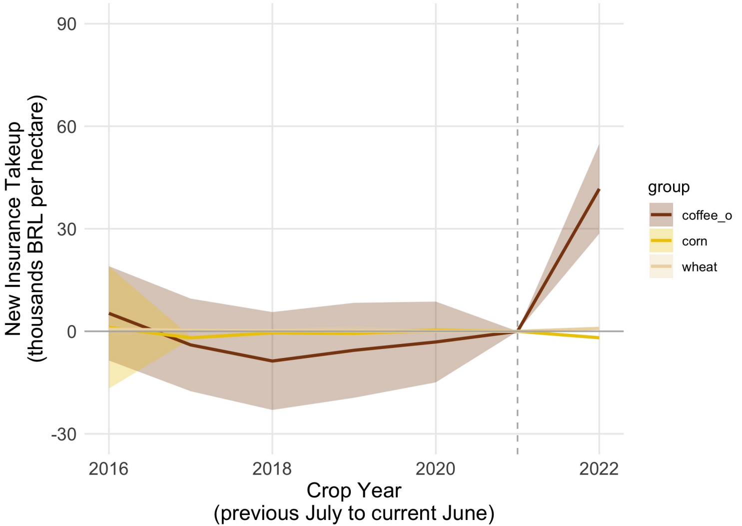


No impact on insurance prices | Unaffected farmers take up more | FX Hedging | Return to Additional Results

Increase in New Insurance Take-Up by Municipality



Unaffected Farmers Purchase More Quantity-Based Insurance



Return

But Affected Coffee Farmers Take Up Less Insurance

Table: Regressions of $\frac{\text{Insured Value (BRL)}}{\text{Area (Hectares)}}$

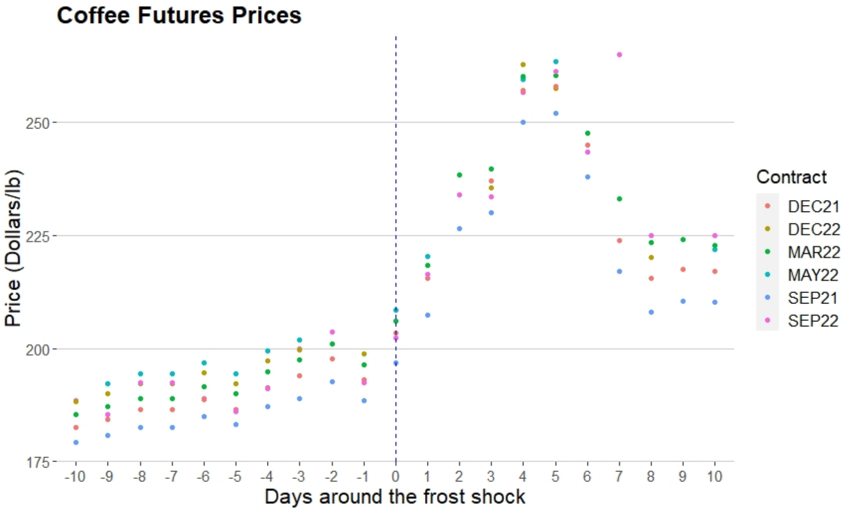
Coffee shock CY 2022	-6552	-9054	-2867
	[-2.8]	[-6.5]	[-2.5]
Corn shock CY 2022	477	-151	217
	[4.3]	[-1.3]	[2.7]
Wheat shock CY 2022	121	105	78
	[1]	[0.5]	[0.5]
Farmer FE	X	X	X
Crop x Year x Muni FE	X	X	
Crop x Year x Muni x Insurer FE			X
Expected output control	X		
Observations	1,840,378	2,359,865	2,334,632

Return

Coffee Prices

Return

Futures Prices Around the Frost Shock



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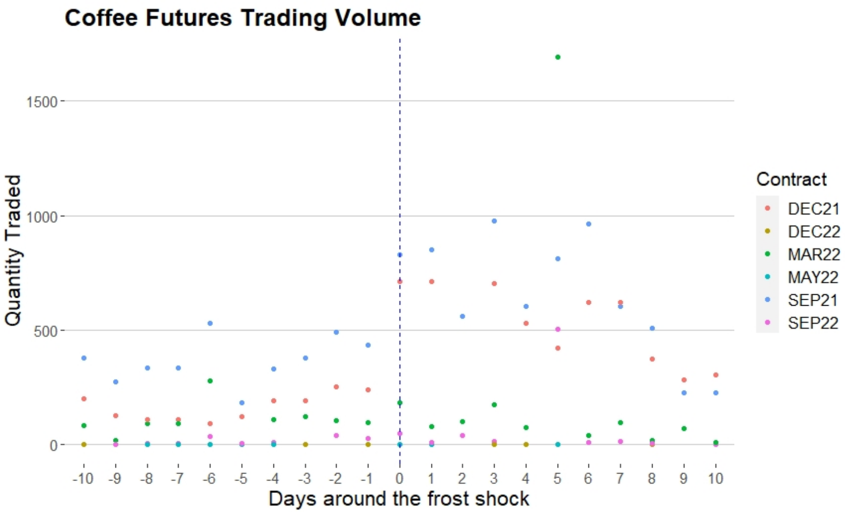
Trading Volume Around the Frost Shock



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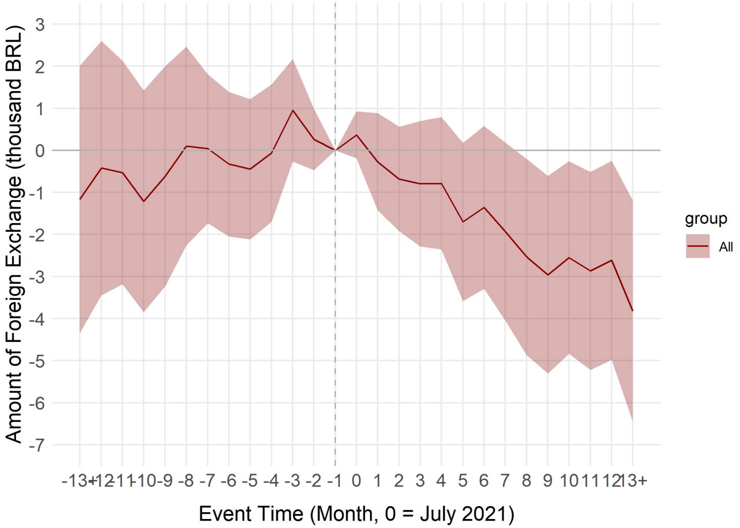
FX Hedging



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