Labor Market Power in Food Retailing

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Recent Policy Trends

Federal government: Grocery mega-merger could raise prices, harm workers

February 27, 2024 | 10:26 AM CST | BY MARK GRUENBERG

FTC, Department of Labor Partner to Protect Workers from Anticompetitive, Unfair, and Deceptive Practices

New agreement establishes formal collaboration between agencies on issues affecting workers

Large Number of Merger Events in Food Retailing

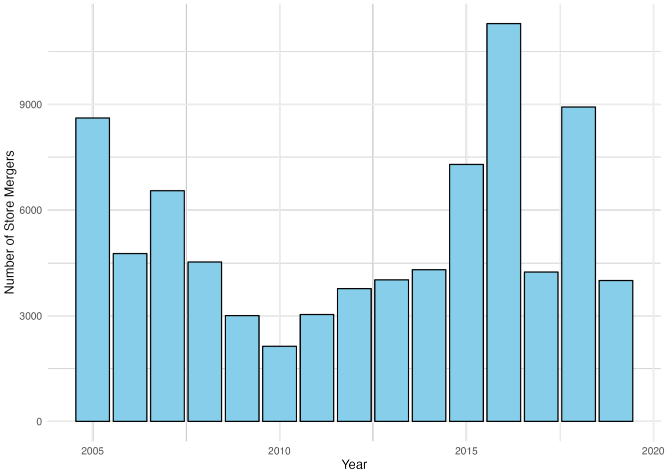

Figure 1: *Note:* 1000s of food stores affected by merger every year. **Data Source:** NielsenIQ TDLinx.

Introduction

- Growing concern about concentration & its effects on workers
  - In 2021, 7.5m retail workers (half of workforce) resigned due to poor pay & conditions.
- Expansion of antitrust policies to include labor market outcomes
- Growing literature on monopsony power via macro & micro lens
- Connection between concentration & labor market power is unclear
  - Identification issues in Neo-Structure-Conduct-Performance approach
  - Concentration measures **potential** for market power, not its exercise
- **Goal:** Estimate labor market power & relate to concentration in US food retail.

What is labor market power?

- Labor market power $=$ labor monopsony power $=$ labor markdown
- Markdown $\equiv$ MRPL/Wage (Manning '03).
- Perfect competition $\Rightarrow$ Markdown $= 1$, $\varepsilon_L = \infty$.
- PC in labor markets is rare:
  - Heterogeneous preferences for workplace amenities, job-switching frictions, mergers, concentration
- Imperfect competition $\Leftrightarrow$ Wages $<$ MRPL $\Leftrightarrow$ Markdowns > 1.
  - Higher monopsony power results in lower wages and higher markdowns (Manning '03; Card '22).

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Research Agenda

Estimate labor market power & relate to concentration in US food retailing industry.

Key questions:

- What are estimates of labor markdowns in US food retailing?
- How do the labor markdowns evolve over time (2004-2019)?
- How do **exercise** of market power (labor markdowns) relate to **potential** for market power (labor market concentration)?

▸ Contributions & Related Literature ▸ Research Strategy

Preview of Results

- Labor markdowns (MRPL/wage) in US food retailing from 2004-2019:
  - Mean markdown: 1.37 (SD = 0.6) $\Rightarrow$ Workers get \$0.73 for \$1 of MRPL.
  - Markdowns are falling $\Rightarrow$ Labor markets getting competitive.
- Relation of markdowns to labor market concentration:
  - 10% rise in concentration leads to 6% to 11% higher markdowns.

▸ Motivation from Minimum Wage Employment Effects

Roadmap of Talk

Data

Model & Estimation

Results

Conclusion

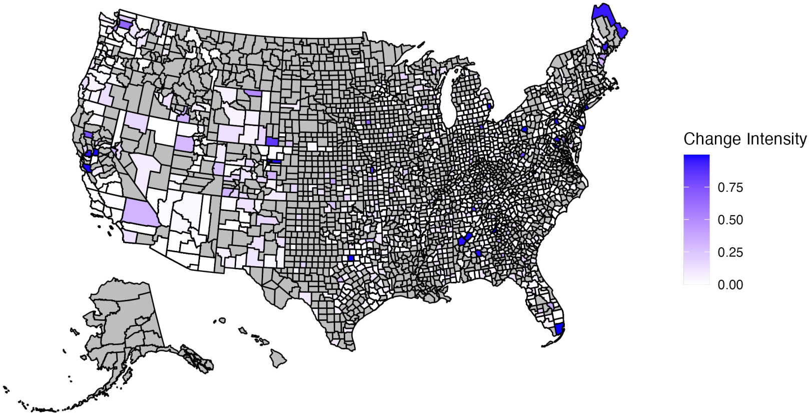
Data — Summary Statistics

Variables	Unit	Source	Mean	St. Dev.	Min	Max
Establishments Count	#	QCEW	76.7	156	1	1,580
Weekly Wage	$	QCEW	427.7	151.1	2	2,713
County Area	Sq Mi	QCEW	1,593.1	2,581.6	26	20,056.9
Income	$ ('000)	Census	55.6	14.7	20.1	151.8
Population	# ('000)	Census	1,150	2,060	3.8	10,095
Unemployment Rate	%	Census	6.1	2.7	1.6	29.4
County Minimum Wage	$/hr	Census	7.5	1.2	5.2	13.3
Merger	Binary	TDLinx	0.01	0.08	0	1
Square Feet	Sq. Ft. ('000)	TDLinx	51.8	18.5	3	224
Firm Age	Years	TDLinx	9.7	5.2	0	20
Checkouts (Capital)	#	TDLinx	18	9.8	1	59.92
COGS (Materials)	$ ('000)	TDL + Compustat	472	227	9.8	2,456
Employment (Labor)	#	TDLinx	191.7	149.3	4	992
Revenue (Output)	$ ('000)	TDLinx	629	309	15	3,300

Table 1: Number of Observations $= 74,929$ for years 2004-2019.

Minimum Wage Motivation for Markdowns

Data — Intensity of Changes in County Concentration



Data — Labor Market Concentration and Wages

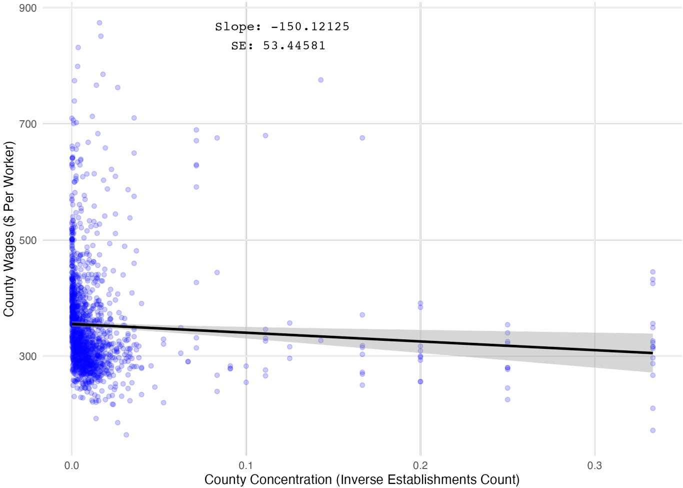


Figure 3: Negative relationship between county concentration & wages. Data: QCEW & Vaghul & Zipperer ('22).

Roadmap of Talk

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- **Goal:** Estimate labor markdowns (MRPL/Wages) in food retailing.

- Main result from production-function literature (E.g., Yeh, Macaluso, & Hershbein '22)

$$\underbrace{\nu_{it}}_{\text{Markdown}} = \left(\underbrace{\frac{\alpha_{it}^{COGS}}{\tau_{it}^{COGS}}}_{\text{Markup}}\right)^{-1} \cdot \underbrace{\frac{\alpha_{it}^{L}}{\tau_{it}^{L}}}_{\text{Labor wedge}} \tag{1}$$

where RHS are ratios of COGS and labor elasticities α to COGS and labor shares of revenue τ.

- Need a *flexible* input, free of adjustment costs & monopsony power. COGS.
  - To separate markdowns & markups from total market power. $\frac{\alpha_{it}^{L}}{\tau_{it}^{L}}$ gives total market power.

- Input shares are in data, & prod. func. estimation for output elasticities.

- IV strategies (SSIV & LOOIV) to find how market concentration impacts markdowns.

Structural Model: Idea

- **Goal:** Estimate labor markdowns (MRPL/Wages) in food retailing.
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Model and Estimation

- To get output elasticities, I estimate a **translog** production function

$$q_{it} = \sum_{k=1}^{3} \alpha_k x_{it}^k + \sum_{k=1}^{3} \alpha_{kk} (x_{it}^k)^2 + \sum_{j,k=1}^{3} \alpha_{jk} (x_{it}^j)(x_{it}^k) + \omega_{it} + \epsilon_{it} \tag{2}$$
$$= f(x_{it}; \alpha) + \omega_{it} + \epsilon_{it}$$

  - Here, q_{it} = log store (i) revenue at time t; x_{it} = vector of log of input expenses **(labor, capital, COGS)**; ω_{it} = productivity shock; α = vector of parameters to be estimated.
  - Translog spec. gives a 2nd-order log approximation to any diff. prod. func. & subsumes Cobb-Douglas.

- Use GMM-IV approach based on Ackerberg, Caves, & Frazer ('15); Yeh, Macaluso, & Hershbein '22 to estimate the output elasticities. Get labor markdowns using equation (1).

▸ Model Details   ▸ Model Estimation GMM-IV

Roadmap of Talk

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Translog Production Function Estimates

	Estimation Method			
	(1)	(2)	(3)	(4)
Capital	0.059*	0.060*	0.056*	0.056*
	(0.035)	(0.034)	(0.031)	(0.032)
Labor	0.169***	0.083***	0.102***	0.089***
	(0.038)	(0.023)	(0.023)	(0.027)
Materials	0.696***	0.772***	0.747***	0.768***
	(0.179)	(0.147)	(0.170)	(0.146)
Returns to Scale	0.925**	0.916**	0.906**	0.915**
	(0.467)	(0.460)	(0.432)	(0.451)
Mean Markdown	2.218	1.067	1.372	1.166
Year FEs	No	Yes	Yes	Yes
FIPS FEs	No	No	Yes	Yes
Controls	No	No	No	Yes
N	74,929	74,929	74,929	74,929

Table 2: Different specifications correspond to first stage (OLS) in GMM-IV procedure. Clustered SE at county level in parentheses. Controls include log of county population, income, unemployment rate. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Markdowns by Channel Category

Channel	Mean	Median	Min	Max	IQR	St. Dev.
Grocery	1.392	1.119	0.108	19.019	1.275	0.598
Mass Merchandiser	1.019	0.945	0.037	14.746	0.468	0.609
Entire Sample (Obs. = 74,929)	1.372	1.116	0.037	19.019	0.701	0.599

Table 3: Summary statistics of store-level markdowns by channel, 2004-2019.

Markdowns by NAICS

NAICS	Mean	Median	Min	Max	IQR	St. Dev.
445110	1.628	1.589	0.008	3.763	1.063	0.799
455219	0.756	0.634	0.039	3.759	0.399	0.518
Entire Sample (Obs. = 74,929)	1.372	1.116	0.037	19.019	0.701	0.599

Table 4: NAICS 445110 refers to "Supermarkets and Other Grocery Stores, Excluding Convenience Stores", and 455219 refers to "All Other General Merchandise Stores".

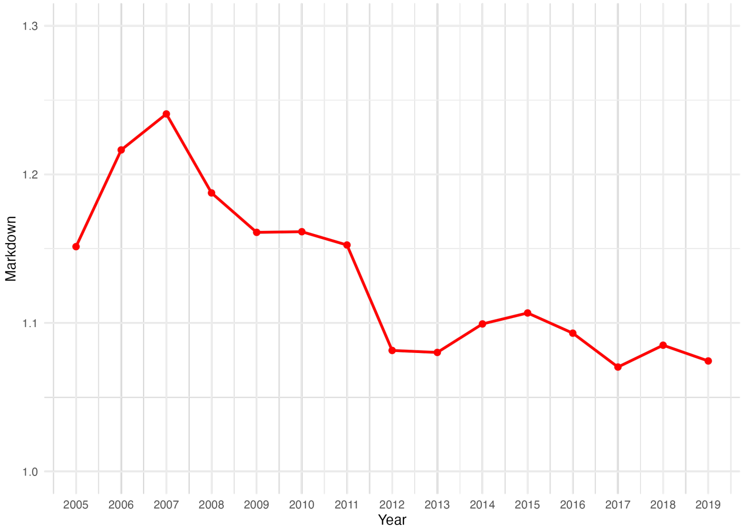
Variance Decomposition

Component	Variance	Relative Contribution
Markdown (ν)	0.598	1.000
Output elasticity (θ_l)	0.070	0.116
Labor share (α_l)	0.293	0.490
Markup (μ)	0.081	0.136
	Covariance	
$\theta_l,\ \alpha_l$	-0.037	-0.125
$\theta_l,\ \mu$	-0.013	-0.044
$\alpha_l,\ \mu$	0.027	0.089

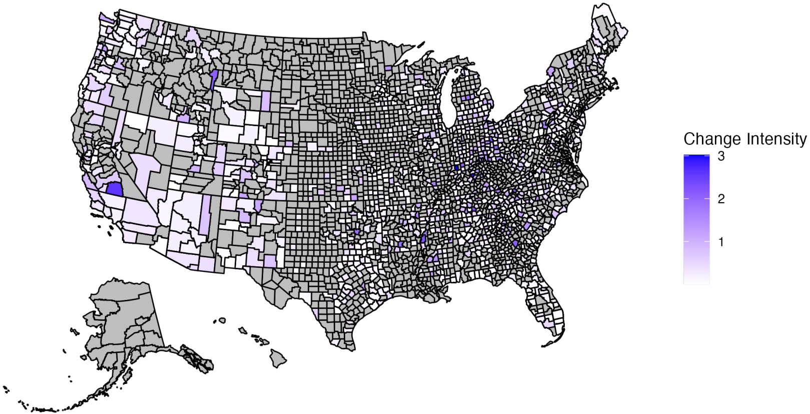
Table 5: Variance decomposition of markdown (ν) into labor elasticity (θ_l), labor share (α_l), and markup (μ).

▸ Evolution of Markups

Evolution of Aggregate Markdowns in US Food Retailing



Intensity of Changes in County Level Labor Markdowns



Labor Market Concentration & Markdowns

IV regression of markdown on HHI w/ LOOIV

	Log Store Markdown		
	(1)	(2)	(3)
Log HHI (LOOIV-Instrumented)	0.6283***	0.6004***	1.098***
	(0.1590)	(0.1551)	(0.3014)
FIPS FEs		Yes	Yes
Controls			Yes
F-test (1st Stage)	417.4***	833.9***	155.4***
Observations	74,929	74,929	74,929

Table 6: $^{***}p < 0.01$. HHI at the FIPS/county level is defined as the inverse of the total number of establishments in the food retail sector. The leave-one-out IV (LOOIV) is the inverse number of employers in all other FIPS and isolates external variations in concentration to address endogeneity.

IV regression of markdown on HHI with SSIV

	Log Store Markdown		
	(1)	(2)	(3)
Log HHI (SSIV-Instrumented)	-0.3081**	1.002***	1.024***
	(0.1048)	(0.1253)	(0.1488)
FIPS FEs		Yes	Yes
Controls			Yes
F-test (1st Stage)	597.7***	46.8***	35.3***
Observations	74,929	74,929	74,929

Table 7: $^{***}p < 0.01$. HHI is defined at the FIPS level as the inverse of the total number of establishments in the food retail sector. The Shift-Share IV (SSIV) is constructed by multiplying the national merger trend (shift) by each FIPS's pre-existing share of establishments (share). This instrument isolates exogenous variation in local market concentration and addresses endogeneity in estimating markdown impacts.

Roadmap of Talk

Conclusion

- Growing concern on labor market concentration and monopsony power.
- Estimate labor markdowns (MRPL/Wages) in US food retailing, 2004-2019.
  - Mean is 1.37, that is workers earn \$0.73 per \$1 generated on the margin.
  - Industry-year mean markdowns are falling over time $\Rightarrow$ labor markets getting competitive.
- Markdowns are greater in concentrated markets.
  - 10% increase in concentration $\Rightarrow$ 6% to 11% increase in markdowns.
- Future work: To expand the data up to 2022, and carry out additional robustness checks of markdown estimates!

Thank you! paudeluj@gmail.com ujjwolpaudel.github.io

Reduced-Form Analysis

- Store $= s$, County $= c$, Year $= t$. ▸ Summary Statistics
- **Store level** employment effects of county-minimum wage:

$$\ln\left(y_{sct}\right) = \alpha_c + \beta_t + \delta \ln\left(MW_{ct}\right) + \mathbf{X}'_{ct}\gamma + \epsilon_{sct} \tag{3}$$

y_{sct} = employment; α_c, β_t = fixed effects; $\mathbf{X}'_{ct}$ = covariates.

- **Moderation effects of labor market concentration:**

$$\ln\left(y_{sct}\right) = \alpha_c + \beta_t + \delta \ln\left(MW_{ct}\right) + \psi HHI_c + \lambda\left[\ln\left(MW_{ct}\right) * HHI_c\right] + \mathbf{X}'_{ct}\gamma + \epsilon_{sct} \tag{4}$$

HHI_c is defined in four ways. ▸ TWFE Results

- Heterogeneity-robust estimator from de Chaisemartin et al. ('24). Ongoing … ▸ dCDH24 Details

Minimum Wage Employment Effects

- TWFE results show positive employment effects in concentrated labor markets. Suggests labor monopsony power (Card & Krueger '94; Azar, Marinescu, et al. '24). ▸ Preview of Results ▸ Reduced Form Analysis

Log Store Employment	(1)	(2)	(3)	(4)
Log Min Wage	0.0849**	0.0868**	0.0921**	0.1883***
	(0.0421)	(0.0418)	(0.0411)	(0.0549)
Log Min Wage $\times$ HHI	0.1462	1.034**	0.1019**	-0.1178**
	(0.1266)	(0.4415)	(0.0430)	(0.0449)
FIPS & Year Fixed Effects	✓	✓	✓	✓
Controls	✓	✓	✓	✓
FIPS Linear Trends	✓	✓	✓	✓
Observations	74,929	74,929	74,929	74,929
R-squared	0.4524	0.4523	0.4523	0.4523

Table 8: ***: 0.01, **: 0.05, *: 0.1.(1) = Inv Est Count. (2) = Inv Pop Density. (3) = Binary(HHI $\geq$ 0.18). (4) = Binary (HHI $<$ 0.1).

Contributions & Related Literature

Research Agenda

- Literature on minimum wage effects on employment
  - Card & Krueger ’94; Dube et al. ’10; Meer & West ’16; Jardim et al. ’18; Cengiz et al. ’19; Clemens & Wither ’19; Azar et al. ’24; …
- Literature on imperfectly competitive labor markets in food retail
  - Food retail is distinct with min. wage workers, ubiquitous grocers, strong consumer-welfare ties.
  - Complements Azar et al. (’20; 22), Arnold (’21), Yeh et al. (’22), Berger et al. (’22), Rubens (’23)
- IO literature on production function estimation
  - Production function approach to infer labor markdowns (Hall ’88; OP ’96; LP ’03; DLW ’12; ACF ’15; Yeh et al. ’22)
  - Assesses impacts of concentration on markdowns.
- Antitrust policies for labor markets
  - Need to consider monopsonistic effects besides monopolistic effects in antitrust. Naidu, Posner & Weyl (’18); The Executive Order (’21); Berger et al. (’23)

Research Strategy

Data, 2004-2022

- **NielsenIQ's TDLinx:** store-level mergers, employment, revenue, # checkout registers, area, location, age, channel
- **Compustat:** capital, COGS national-level publicly trading grocers
- **QCEW:** county-industry wages, employment, # establishments
- **Min Wages:** Vaghul & Zipperer '22
- **US Census:** county-level attributes

Estimation Approach

- Effects of minimum wages on store-employment at concentrated labor markets
  - Two-way fixed effects
  - de Chaisemartin et al. ('24) [ongoing ...]
- Production function estimation approach to get the labor markdowns
  - Provides gaps between wages and worker's marginal productivity
  - Structural effects of concentration on markdowns

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Details in Production Function Approach

- Issue in $q_{it} = f(x_{it}; \alpha) + \omega_{it} + \epsilon_{it}$ is ω_{it} is observed to firm but not econometrician.
  - Endogeneity issues: sample selection + simultaneity.
  - Olley & Pakes ('96) use investment as a proxy for ω_{it}.
  - Levinsohn & Petrin ('03) use materials as proxy.
  - Ackerberg, Caves, & Frazer ('15) refine both OP and LP methods in a 3-step GMM-IV approach.
- Main ideas from GMM-IV estimation approach:
  - Use lagged inputs as instruments since they should be uncorrelated with current productivity shocks
  - Define moment conditions based on orthogonality restrictions
  - Estimate production parameters by minimizing quadratic objective function

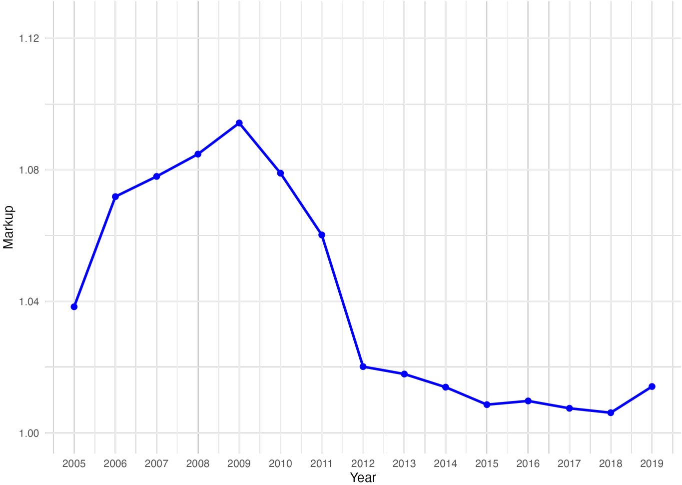
Model & Estimation Idea

PF Model Estimation — GMM-IV Approach

- We have: $q_{it} = f(x_{it}; \alpha) + \omega_{it} + \epsilon_{it} = \phi_{it} + \epsilon_{it}$. ▸ Model & Estimation Idea
- **Step 1:** Estimate ϕ_{it} and ε_{it} by approximating q_{it} with a third degree polynomial in $\tilde{x}_{it} = (k_{it}, l_{it}, m_{it})'$ with interaction terms.
  - Let its fitted values and residuals be denoted by $\hat{\phi}_{it}$ and $\hat{\varepsilon}_{it}$ respectively.
- **Step 2:** Construction of Productivity Innovations
  - Assume ω_{it} is a Markovian process: $\omega_{it} = g_t(\omega_{it-1}) + \xi_{it}$. Have $\omega_{it}(\alpha) = \phi_{it} - f(x_{it}; \alpha)$ from step 1.
  - Approximate productivity evolution $g_t(.)$ with a third-order polynomial in its lagged value: $\omega_{it}(\alpha) = \Omega_{it-1}(\alpha)'\rho(\alpha) + \xi_{it}$
  - Construct innovations as: $\xi_{it}(\alpha) = \omega_{it}(\alpha) - \Omega_{it-1}(\alpha)'\hat{\rho}(\alpha)$, and obtain $\hat{\rho}(\alpha)$ estimates using OLS.
- **Step 3:** Define instrument z_{it} containing lagged values of polynomial terms with l_{it}, m_{it} and k_{it} (keeping capital at k_{it}), and set moment conditions: $E(\xi_{it}(\alpha) z_{it}) = 0$
  - Estimate α by minimizing: $\hat{\alpha} = \text{argmin} \sum [\xi_{it}(\alpha) z_{it}]^2$

Evolution of Aggregate Markups in US Food Retailing

▸ Back



de Chaisemartin et al. ('24): Details

Back

- For county i and time t, D_{it} = log minimum wage, Y_{it} = log retail price index
- **Three-Step Estimation:**
  - **Stayers (counties w/o mw changes)**: Estimate $\Delta Y_{it} = Y_{it} - Y_{i,t-1}$ non-parametrically as $f(D_{i,t-1})$
  - **Switchers (counties w/ mw changes)**: Compare observed ΔY_{it} to predicted $\hat{E}(\Delta Y_{it}|D_{i,t-1}, S = 0)$
  - **Average Treatment Effect:**

$$\hat{\delta} = \frac{1}{n_s} \sum_{i:S_i=1} \frac{\Delta Y_{it} - \hat{E}(\Delta Y_{it}|D_{i,t-1}, S = 0)}{\Delta D_{it}}$$

    where $S_i = 1$ the minimum wage changed for county i (switchers) and 0 otherwise (stayers), $\Delta D_{it} = D_{it} - D_{i,t-1}$ represents the change in the minimum wage, and $n_s = \#\{i : S_i = 1\}$ is the number of switchers in the study period 2011-2021.
- **Implementation Method:** Series estimators with polynomial fits to estimate the relationship between the change in retail price index & the baseline mw.

Double ML Approach for Heterogeneous Treatment Effects

Back

- **Notation:** $D =$ log minimum wage, $Y =$ log retail price index
- **Three-Step DML Estimation:**
  - **Step 1**: Predict Y and D using covariates X via ML algorithms

$$\widehat{\mathbf{E}[Y \mid X]} \text{ and } \widehat{\mathbf{E}[D \mid X]}$$

  - **Step 2**: Compute residuals

$$\widehat{U} = Y - \widehat{\mathbf{E}[Y \mid X]} \text{ and } \widehat{V} = D - \widehat{\mathbf{E}[D \mid X]}$$

  - **Step 3**: Estimate treatment effect

$$\widehat{\alpha} \text{ from regressing } \widehat{U} \text{ on } \widehat{V}$$

where Y is log retail price index, D is log minimum wage, and X includes firm and county covariates. The data-generating process follows:

$$Y = \alpha D + f(X) + U, \quad \mathbf{E}[U \mid X, D] = 0$$

$$D = m(X) + V, \quad \mathbf{E}[V \mid X] = 0$$

- **Implementation Approach:** ML algorithms for prediction steps $\Rightarrow$ we get $\widehat{\alpha}$ as a function of X. Then we perform heterogeneity analysis along covariates.