

Economics 742 Bonus Macro-Labor Lecture 5: Wage Dispersion and Jobless Recoveries

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Spring 2020

Wage Dispersion and Jobless Recoveries

1. Wage Dispersion: Hornstein, Krusell, and Violante (2011)
2. Jobless Recoveries: Facts
3. Turnover
 - Davis and Haltiwanger (2014), Decker et al. (2014), Faberman (2012)
 - Haltiwanger, Jarmin, and Miranda (2013)
 - Puglsey and Sahin (2015)
4. Wage Polarization
 - Jaimovich and Siu (2014)
5. Trading Down and Labor Intensity
 - Jaimovich, Rebelo, and Wong (2017)

Wage Dispersion

- One implication of search that has received quite a bit of attention is wage dispersion.
 - Observably identical workers end up with different wages.
 - Some get “lucky” in search.
 - Others accept a job that is near reservation wage.
- Accords with literature on “residual wage inequality.”
 - Regress wages on observables in Mincerian tradition and find large residual.
 - But big issue of unobservables.
- Hornstein, Krusell, and Violante (2011) unify literature on wage dispersion arising from search.
 - In the process throw a lot of cold water on it.

Hornstein et al. (2011): Mean-Min Wage Ratio

- Recall our basic McCall model adding a separation rate λ :

$$w_R = b + \frac{\alpha}{r + \lambda} \int_{w_R}^{\infty} (w - w_R) dF(w)$$

- Let $\bar{w} = E[w | w > w_R]$ and let $b = \rho \bar{w}$ and $f = \alpha(1 - F(w_R))$ be the job finding rate:

$$w_R = \rho \bar{w} + \frac{f}{r + \lambda} [\bar{w} - w_R]$$

- The *mean-min wage ratio* $Mm = \bar{w}/w_R$ is then:

$$Mm = \frac{\frac{f}{r+\lambda} + 1}{\frac{f}{r+\lambda} + \rho}$$

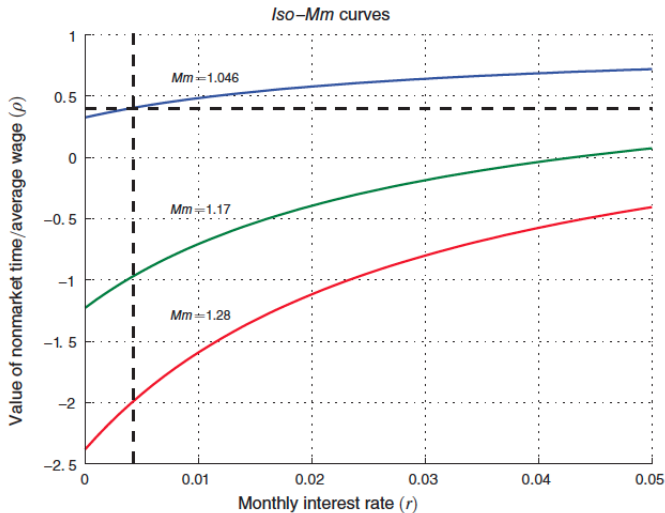
Hornstein et al. (2011): Mean-Min Wage Ratio

- The mean-min wage ratio measures frictional dispersion.
- Crucially, it does not depend on the wage offer distribution.
- This formula holds regardless of the GE closures that determine f , λ , and $F(w)$.
- Back of the envelope calculation:
 - Monthly, $r = .0041$, $\lambda = .03$, $f = .43$.
 - Higher b reduces mean-min, so go with Shimer $\rho = .4$.

$$Mm = \frac{\frac{f}{r+\lambda} + 1}{\frac{f}{r+\lambda} + \rho} = \frac{\frac{0.43}{0.0341} + 1}{\frac{0.43}{0.0341} + 0.4} = 1.046$$

- Wage dispersion is quantitatively insignificant!
 - 50-10 percentile ratios for residual wage dispersion (lower bound) are usually 1.7-1.9.

Hornstein et al. (2011): Mean-Min Wage Ratio



Hornstein et al. (2011): Mean-Min Intuition

- People find jobs quickly.
- The fact that they are accepting a job quickly means there must be low option value to searching longer.
- This option value of searching longer is directly related to observed wage dispersion.
 - The average wage of a job would accept relative to your reservation wage is:

$$E[w - w_R | w > w_R]$$

- This enters into the surplus one could gain through additional search.
- The mean-min wage ratio is just a transformation of this and is thus proportional to the option value of search.

Hornstein et al. (2011): Permutations

- Hornstein, Krusell, and Violante then go through a number of theories that amplify wage dispersion that have been proposed in the literature.
 - None raise Mm ratio substantially.
1. Costly search and endogenous effort ($Mm = 1.088$).
 2. Stochastic wages e.g. Mortensen and Pissarides (Mm virtually unchanged).
 3. Returns to Experience ($Mm = 1.076$).
 4. Risk Aversion ($Mm = 1.88$ if CRRA is 10).
 5. Directed Search ($Mm^{directed} \leq Mm^{undirected}$).
 6. Job Ladder e.g. Burdett and Mortensen (Mm up to 1.27).
 - Most promising path: When leave unemployment do not forgo option value of search.

Hornstein et al. (2011): Sequential Auctions

- The one thing that does very well is sequential auctions as in Cahuc et al. (2006) (recall Jarosch uses this).
 - On the job search creates large amounts of wage dispersion due to stochastic “negotiation capital” from outside offers.
 - This is weakly related to the incentives for an unemployed worker to search for a job.
 - Better than Burdett and Mortensen (1998) because BM have indifference as force pushing against dispersion.
- Can explain dispersion in data if worker bargaining power low.
- Hornstein, Krusell, Violante critique: “Although...undoubtedly a good representation for certain high-skill occupations (e.g., academic jobs), it does not appear to be a wide-spread mechanism for wage setting in the labor market at large.”

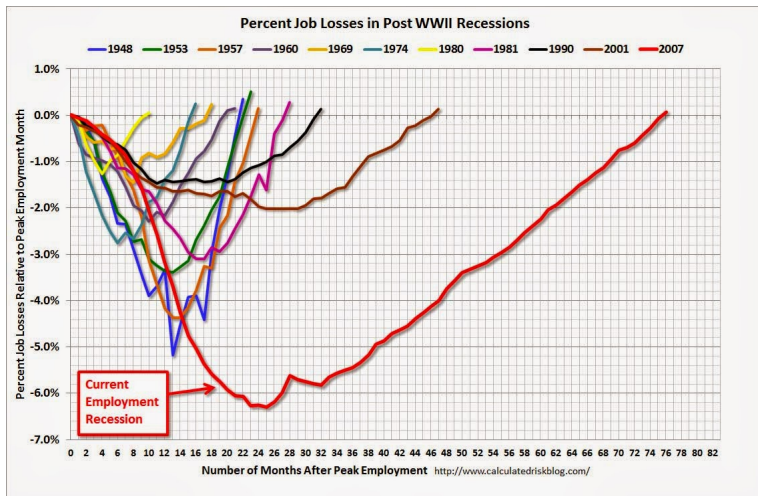
Hornstein et al. (2011): Structural Models

- Paper has important implications for structural estimation of search models.
- In order to match data, typically allow for:
 - “Free parameters” that stray from plausible values.
 - Value of non-market time (ρ here).
 - Discount rates.
 - Unobserved heterogeneity or measurement error that is arbitrary and large.
- Reason is to match dispersion in data with model! Parameters that determine the Mm ratio are exactly what is out of line!
- Because of Hornstein et al. (2011), sequential auctions along with calibrating to Mm is frequently used.
 - For instance, Jarosch (2014) uses Mm ratio as moment.

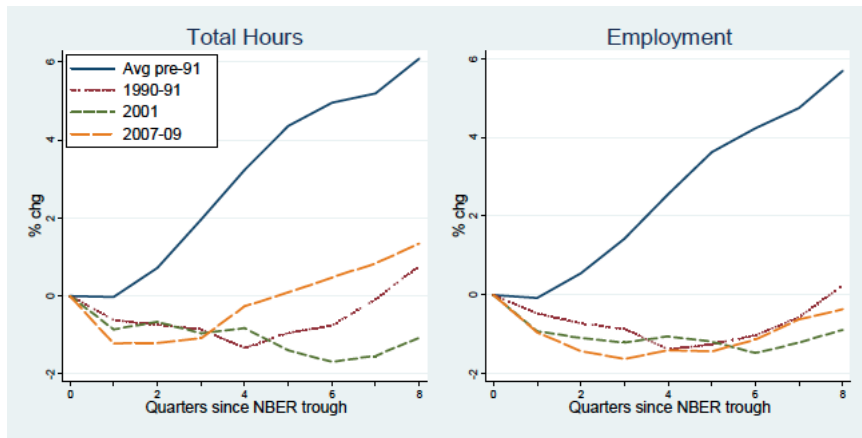
Jobless Recoveries

- I want to close the class by discussing “Jobless Recoveries.”
- Recoveries since 1982 recession have been more gradual, output has recovered faster than employment.
 - “Change” in Okun’s Law.
- Why? Important question.
 - We know little.
 - Hard to say exactly what has changed since do not have great data on older recessions.
- Lecture will inherently be speculative.
 - Will allow me to highlight some puzzles and questions in macro-labor that I find interesting and “advertise” a few papers.
 - Will not be exhaustive.

Jobless Recoveries: Employment in Post-War Recessions

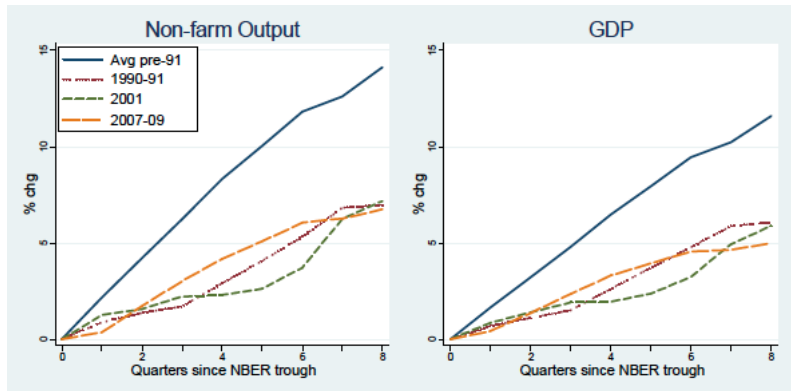


Hours and Employment Post-Trough



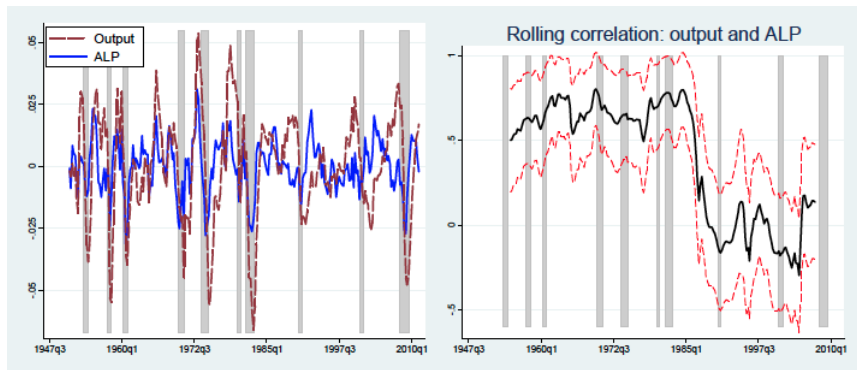
Source: Berger (2012)

Slower Growth Post-Trough Explains Part



Source: Berger (2012)

Change in Corr Between Output and Labor Productivity



Source: Berger (2012). See also Gali and Gambetti (2009) and Gali and Van Rens (2010)

Jobless Recoveries: Some Theories

1. Bachmann (2012): Adjustment costs on extensive margin \Rightarrow employment high at end of short and shallow recession.
 - Depth of recessions changed (pre Great Recession paper).
2. Berger (2016): Firms streamline and restructure in recessions by laying off unproductive workers.
 - Union strength changed.
3. Garin, Pries, and Sims (2013): Great moderation \Rightarrow reallocative shocks more important, aggregate less important.
 - “Great moderation” was the change.
4. Fed policies after Volcker disinflation change cyclical dynamics.
 - Monetary policy changed.
5. Different shocks: recent cycles driven by asset bubbles.

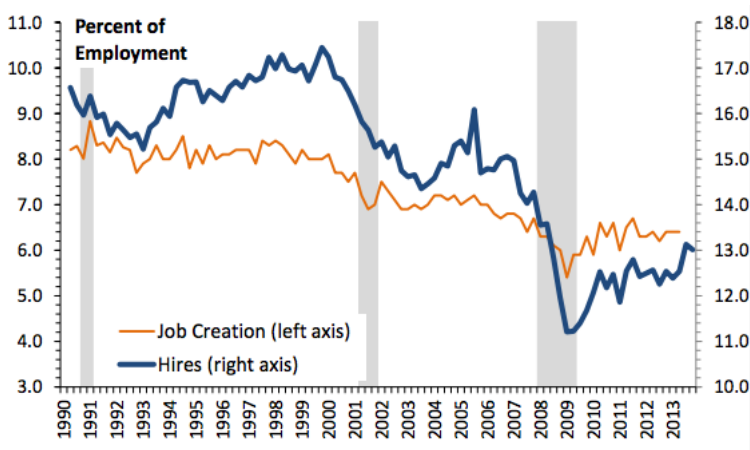
Jobless Recoveries: What I Will Cover

- 3 Sets of papers that provide interesting facts that have yet to be fully explained and may be related to jobless recoveries.
1. Declining Turnover: Davis and Haltiwanger (2014), Decker et al. (2014), Faberman (2012), Pugsley and Sahin (2014).
 2. Job Polarization: Jaimovich and Siu (2014).
 3. Quality Ladders and Labor Intensity: Jaimovich, Rebelo, and Wong (2014).

Decline in Labor Market Fluidity

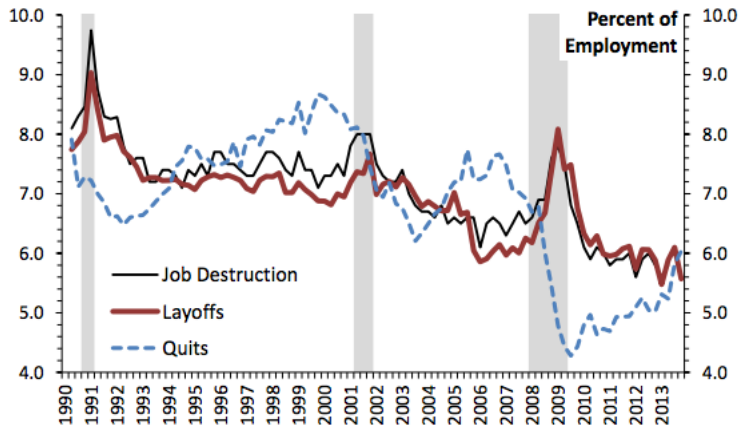
- Labor market fluidity has been declining steadily for last 25 years, possibly longer.
 - Whether measured as reallocation of jobs or workers
 - Pervasive trend across states, industries, demographic groups.
- Big effects.
 - Job reallocation rates fell by more than a quarter since 1990.
 - Worker reallocation rates fell by more than a quarter since 2000.
- See Davis and Haltiwanger (2014) for a review.
 - Faberman (2012) stitches together data to 1947 and finds secular trend since 1960s.

Decline in Labor Market Fluidity



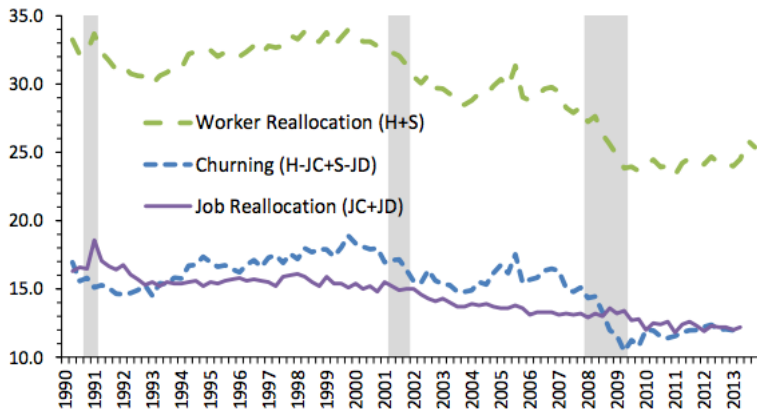
Source: Davis and Haltiwanger (2014)

Decline in Labor Market Fluidity



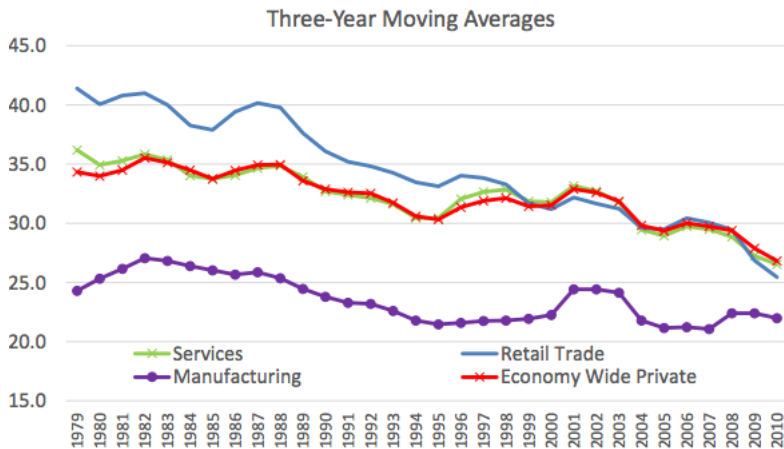
Source: Davis and Haltiwanger (2014)

Decline in Labor Market Fluidity



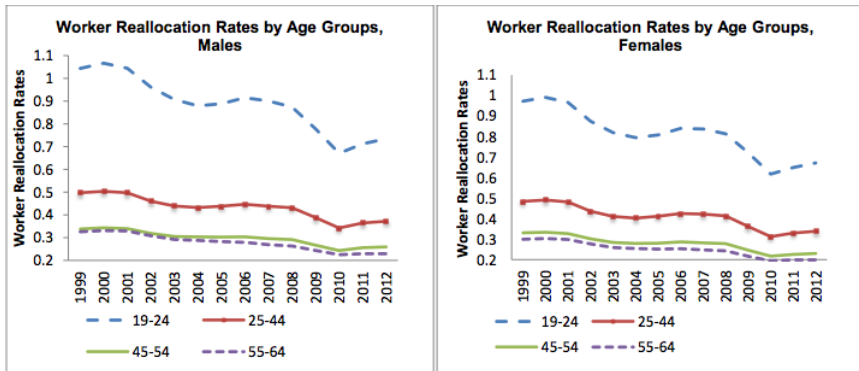
Source: Davis and Haltiwanger (2014)

Decline in Labor Market Fluidity



Source: Davis and Haltiwanger (2014)

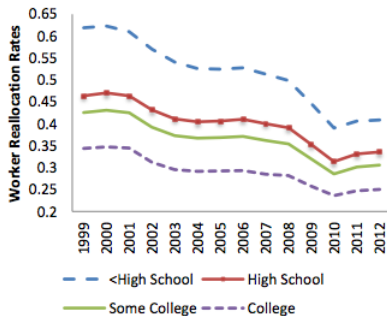
Decline in Labor Market Fluidity



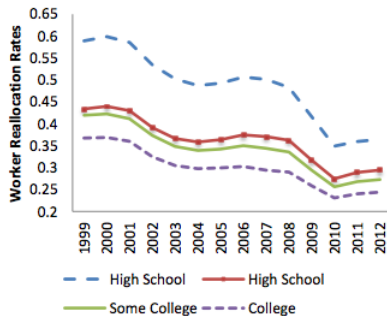
Source: Davis and Haltiwanger (2014)

Decline in Labor Market Fluidity

Worker Reallocation Rates by Education, Males

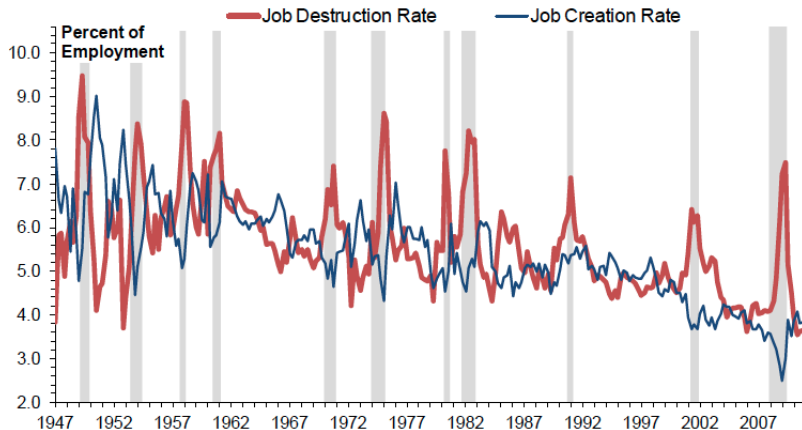


Worker Reallocation Rates by Education, Females



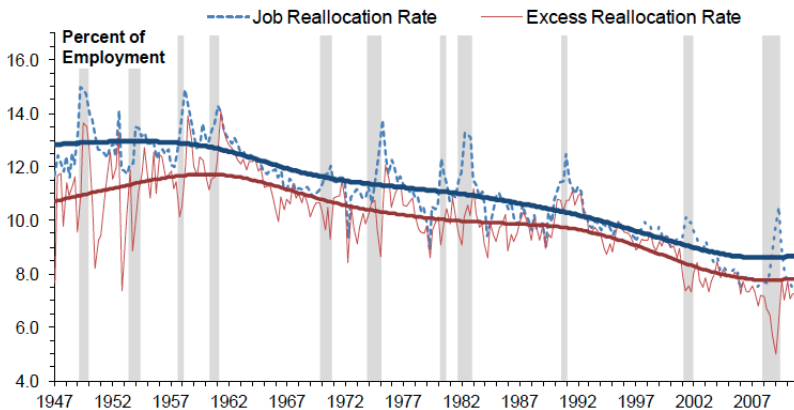
Source: Davis and Haltiwanger (2014)

Decline in Labor Market Fluidity



Source: Faberman (2012)

Decline in Labor Market Fluidity



Source: Faberman (2012)

Effects of Decline

- Davis and Haltiwanger argue decline in fluidity is bad for employment and wages.
 - Slower arrival rate of job opportunities.
 - Slower job ladder.
 - Less learning in Jovanovic (1979) sense \Rightarrow worse “sorting” of workers to jobs.
 - Leads to more sluggish cyclical responses.
 - See below.

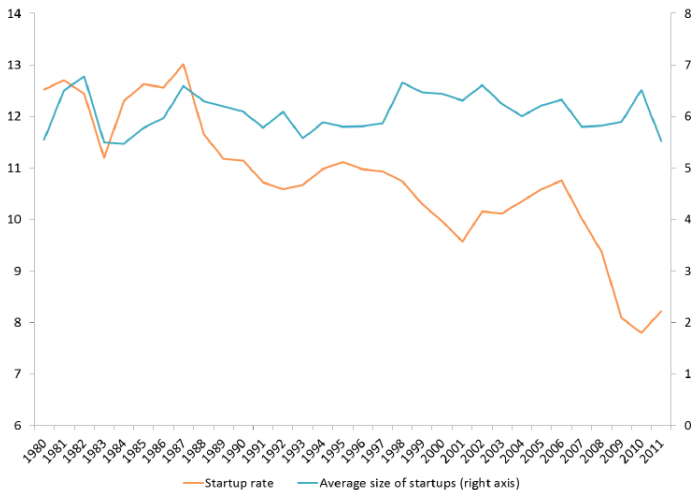
What Explains the Decline?

- Davis and Haltiwanger (2014) discuss several explanations.
- 1. Aging workforce. Young turn over more.
 - But really the very young (teens and 20s), so baby boom retirement has small effect.
- 2. Aging “firmforce.” Shift away from young and small employers that are typically dynamic.
 - About 1/4.
- 3. Rest is waiting for a good explanation.
 - Cairo (2013): Increase in on-the-job training and specific human capital.
 - Some speculation about regulations and policies that hamper reallocation.
- Note: Decker et al. (2014) show industry goes the wrong way (manufacturing is low turnover, retail and services higher).

Firm Age and Job Creation

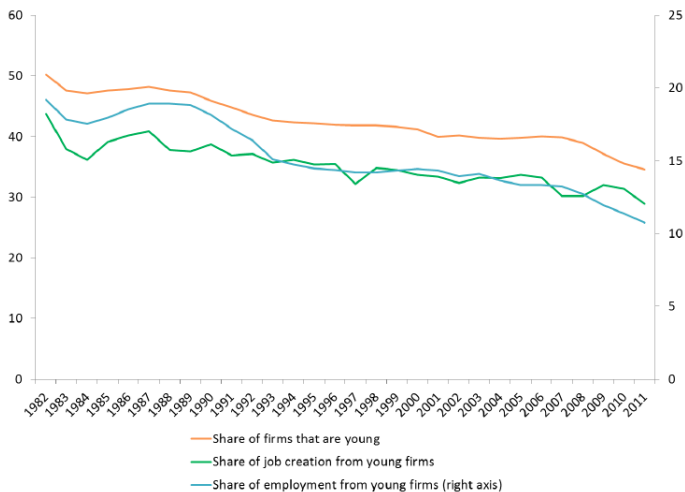
- Worth talking a bit more about the aging firmforce argument.
- Folk wisdom: Small firms fuel business dynamism.
 - Create lots of jobs, but many fail.
- Haltiwanger, Jarmin, and Miranda (2013) amend.
 - True, but once you condition on firm age, firm size does not matter.
 - Strong “up or out” dynamic for young firms is key force in business dynamics.
 - Startups are key for aggregate employment growth.
- Decker et al. (2014) show startup rate has fallen dramatically.
 - Small fraction of employment (fell from 6% to 3% since 1970s) but large fraction of growth.

Decline in Startup Rate



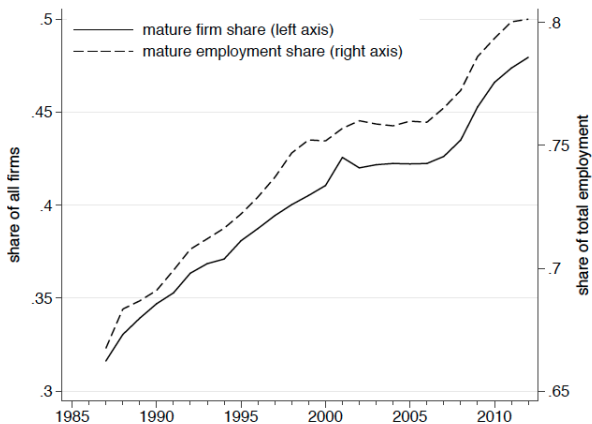
Source: Decker et al. (2014)s

Decline in Young Firms



Source: Decker et al. (2014)

Growth in Mature Firms



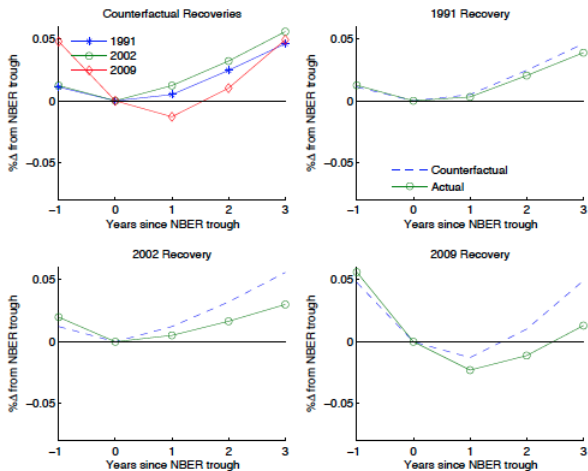
(b) Mature (ages 11+) shares from 1987 to 2012

Source: Pugsley and Sahin (2014)

“Grown Up Business Cycles”

- Pugsley and Sahin (2015) study this aging of the firmforce.
 - Survival and growth margins have remained stable.
 - Entire aging of firmforce is due to *startup deficit*. Holds across states and industries.
- Create counterfactual employment without startup deficit.
- Can explain jobless recoveries.
 1. Aging of firms decreases cyclical sensitivity.
 2. Decline in firm entry amplifies output contractions and reduces growth in booms.
- Leads to downturns that look similar (perhaps a bit worse if #2 wins), but recoveries that appear jobless due to both factors.

Growth in Mature Firms



Source: Pugsley and Sahin (2015)

Vacancy Yield Margin

- One other paper you should be aware of: Davis, Faberman, and Haltiwanger (2013).
- Use JOLTs microdata. Decompose hires into new vacancies and vacancy fill rate.
 - Find fill rate is important.
 - Moves against employment.
 - Huge cross-sectional dispersion. Rises steeply with establishment growth rates.
- Shifts focus to other hiring tools besides vacancies. In particular, “recruiting intensity.”
 - Decrease in intensity explains shifts in Beveridge curve.
 - Intensity explains large share of fluctuations in aggregate hires.
- Gavazza, Mongey, and Violante (2016) try to match these facts in a model.

Recruiting Intensity

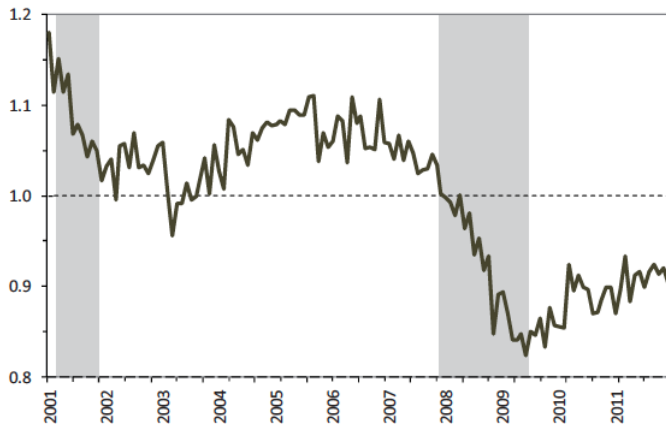
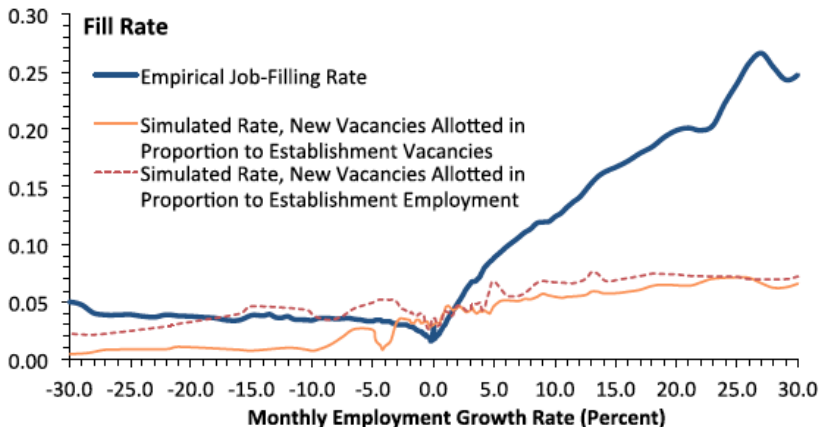


FIGURE X

Index of Recruiting Intensity Per Vacancy, January 2001 to December 2011

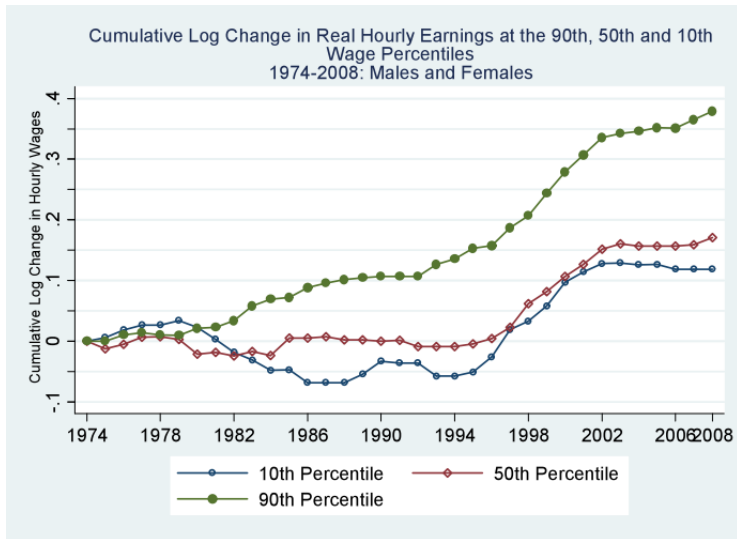
Standard Models Fail to Explain Why Growth So Strongly Correlated With Fill Rate



Wage Polarization

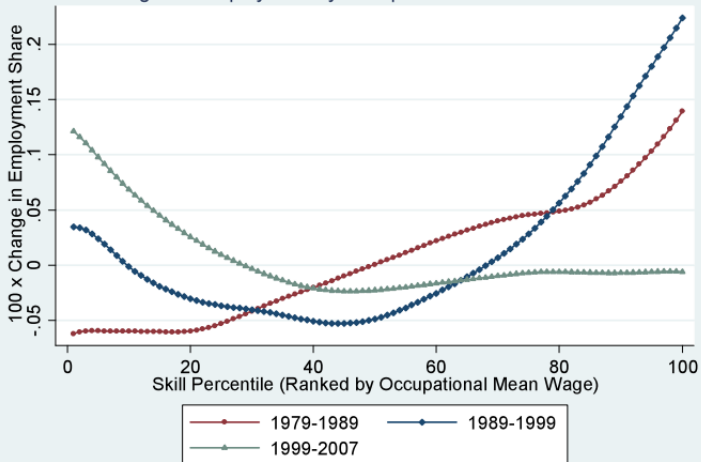
- Perhaps the dominant trend in labor markets in the last 40 years is an increase in inequality.
 - Initially widening college wage premium.
 - Recently job polarization, as the extremes do better than the middle (Acemoglu and Autor, 2011).
 - Polarization driven by automation of “routine” jobs.
- Jaimovich and Siu (2014) link to jobless recoveries.
 - “Essentially all” of jobless recoveries driven only by disappearing routine jobs.
 - Present band pass filtered time series.
 - Model based on middle-skill workers leaving routine jobs to train to be a high skill worker.
 - Foote and Ryan (2014) challenge using flows data.

Job Polarization

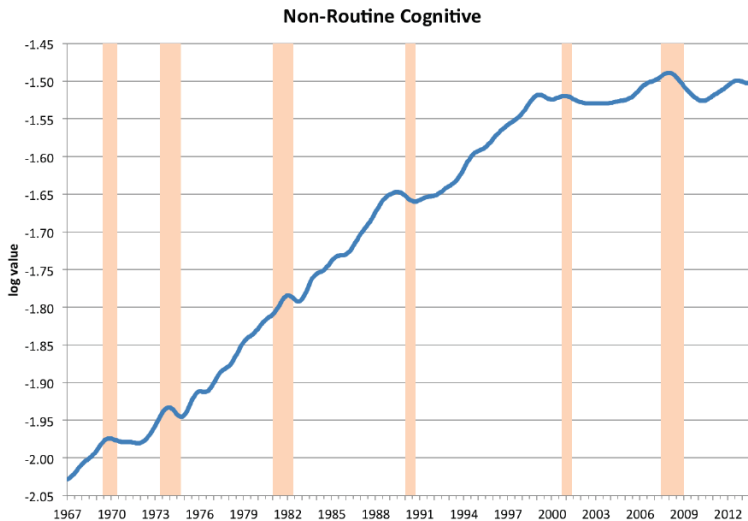


Job Polarization

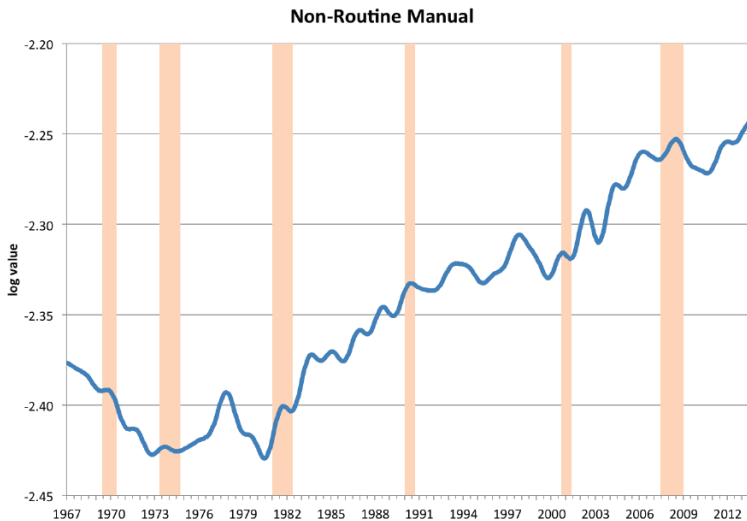
Smoothed Changes in Employment by Occupational Skill Percentile 1979-2007



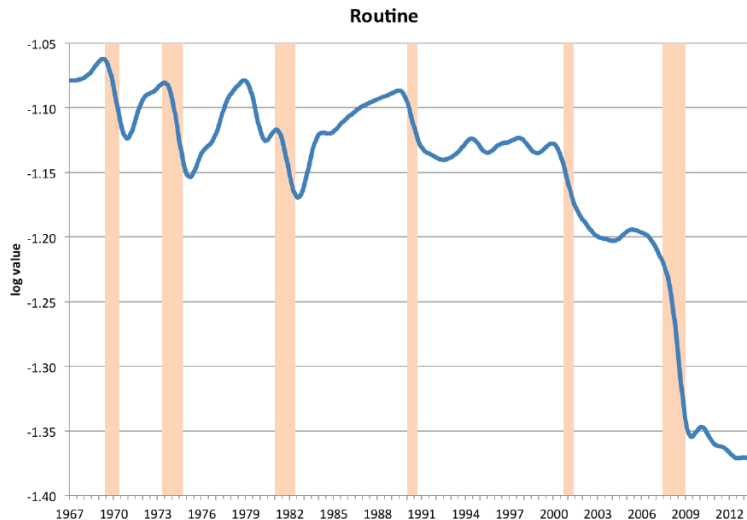
Non-Routine Cognitive Since 1967



Non-Routine Manual Since 1967



Routine Since 1967



Thoughts on Wage Polarization

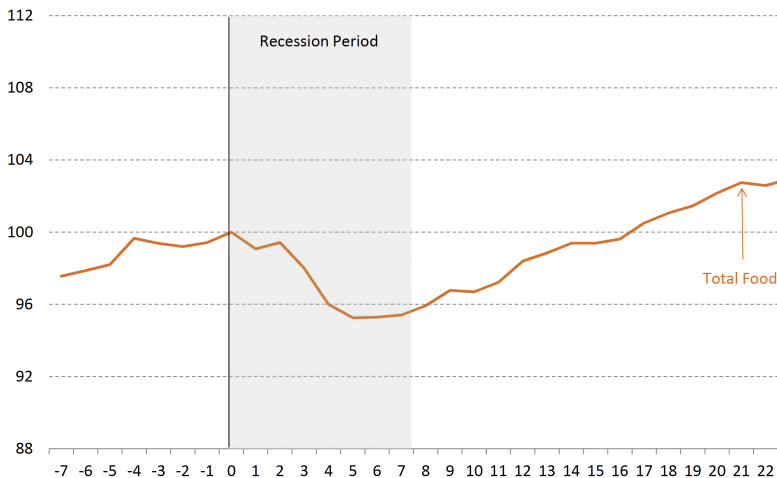
- I think this is a fascinating fact.
 - How does this relate to the decline in manufacturing (Charles, Hurst, and Notowidigdo, 2013)? To trade with China (Acemoglu et al., 2014)?
 - Is this true for everything within the “routine” category? What is driving it?
- Hard to fit into simple economic model.
 - Does this fit with “cyclical restructuring” story (e.g. Berger, 2016)? How does it relate to the literature on whether business cycles are cleansing or sullyng? (e.g. Caballero and Hammour, 1994; Barlevy, 2002).
 - Like idea of interaction between cycle and secular trends.
- More work should be done on this.

Trading Down and the Business Cycle

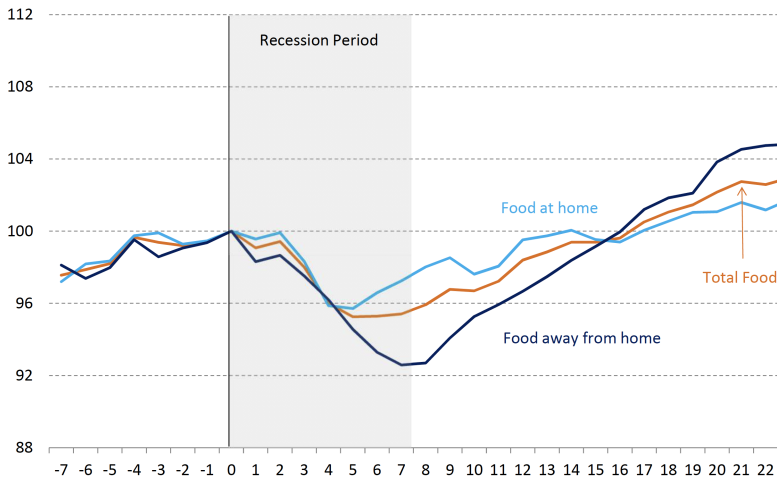
- Jaimovich, Rebelo, and Wong (2017)¹ present another intriguing explanation.
- In recent decades, real incomes have stagnated.
 - Argue that one important way households have responded is by “trading down” on the quality margin.
 - Happens particularly in recessions.
- These lower quality goods are less labor intensive.
 - Reduces aggregate labor demand in recessions.
- Consumption side of secular trends story.
- They have model, but I will focus on facts.

¹These slides draw on Jaimovich, Rebelo, and Wong’s slides, which are gratefully acknowledged.

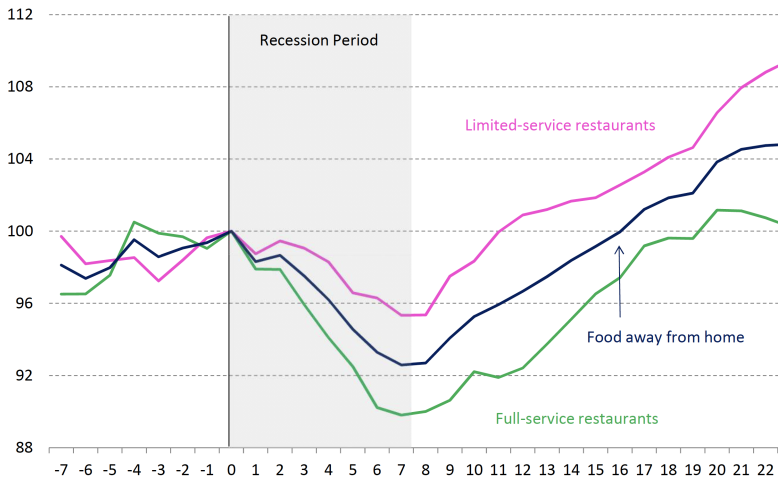
Basic Story: Food



Basic Story: Food



Basic Story: Food



Jaimovich et al. (2017): Data

- How do you get detailed data on quality and labor share?
 - Jaimovich, Rebelo, and Wong have to be very clever!
- Create data set with firm-level measures of quality, labor intensity, and market share.
 - Assume quality is correlated with price.
 - Get prices from PPI micro data (manufacturing) and Yelp (consumer goods).
 - Link to Compustat and Census of Retail Trade to get market shares and labor intensities.
 - Check everything with detailed consulting group data on restaurant spending by level of quality and with consumption data.

Yelp, Census of Retail Trade, Compustat Matched Data

Table: Market shares and Labor Intensity: 2007

Industry	\$m Sales	Labor intensity			Market share		
		Low	Middle	High	Low	Middle	High
Home furnishing and appliances	654,535	4.40	4.97	7.10	1%	95%	5%
Grocery stores	547,837	3.37	4.68	7.58	39%	59%	2%
Food services and drinking places	444,551	15.63	24.02	22.43	52%	41%	7%
Clothing stores	221,205	7.55	9.43	16.49	11%	78%	11%
General merchandise stores	578,582	3.72	6.92	7.19	64%	23%	13%
Total	2,446,710	6.33	9.23	10.86	35%	58%	7%

Yelp, Census of Retail Trade, Compustat Matched Data

Table: Market shares and Labor Intensity: 2012

Industry	\$m Sales Census	Labor intensity			Market share		
		Low	Middle	High	Low	Middle	High
Home furnishing and appliances	609,323	3.49	4.92	5.93	1%	94%	5%
Grocery stores	631,486	1.92	4.15	6.06	43%	53%	5%
Food services and drinking places	524,892	13.43	19.49	22.40	61%	33%	6%
Clothing stores	241,386	6.50	9.16	15.09	15%	77%	7%
General merchandise stores	649,754	3.72	6.92	7.19	72%	18%	10%
Total	2,656,841	5.41	8.49	10.36	42%	52%	6%

Change in Market Share by Quality Tier

Sector	Low	Middle	High
Home furnishing stores	0.1%	-0.5%	0.4%
Grocery stores	3.9%	-6.4%	2.6%
Restaurants	8.6%	-7.9%	-0.6%
Apparel stores	4.3%	-0.6%	-3.7%
General merchandise stores	8.5%	-4.8%	-3.8%
Overall	7%	-6.5%	-0.5%

Actual Employment Changes

Sector	Low	Middle	High	Total
Home furnishing stores	7	-947	-74	-1,014
Grocery stores	99	-291	40	-152
Restaurants	1,613	-1,882	101	-167
Apparel stores	1	-231	-92	-322
General merchandise stores	408	-276	-72	61
Total	2,105	-3,635	-214	-1,744

Estimate: Change in Employment Without Trading Down

$$\log\left(\frac{N_{t+1}}{N_t}\right) = \log\left(\frac{Y_{t+1}}{Y_t}\right) + \log\left(\sum_{m=1}^M \frac{Y_{m,t+1}}{Y_{t+1}} \sum_{j=1}^J S_{j,m,t+1} L_{j,m,t+1}\right) \\ - \log\left(\sum_{m=1}^M \sum_{j=1}^J \frac{Y_{m,t}}{Y_t} S_{j,m,t} L_{j,m,t}\right)$$

$$\log\left(\frac{N_{t+1}^{CF}}{N_t}\right) = \left(\log \frac{Y_{t+1}}{Y_t}\right) + \log\left(\sum_{m=1}^M \frac{Y_{m,t+1}}{Y_{t+1}} \sum_{j=1}^J \textcolor{red}{S}_{j,m,t} L_{j,m,t+1}\right) \\ - \log\left(\sum_{m=1}^M \frac{Y_{m,t}}{Y_t} \sum_{j=1}^J S_{j,m,t} L_{j,m,t}\right)$$

- Employment fell 3.39%.
- In counterfactual without trading down only 0.39%.

PPI and Compustat Matched Data

Table: Market shares and Labor Intensity: 2007

Industry	\$m Expenditure in 2007	Labor Intensity			Market share		
		Low	Middle	High	Low	Middle	High
31	811,751	0.74	3.41	n.a.	23%	77%	n.a.
32	1,434,885	2.73	2.99	4.62	26%	45%	29%
33	2,457,336	2.04	2.60	4.05	31%	63%	6%
Total	4,703,972	2.03	2.86	3.53	28%	58%	14%

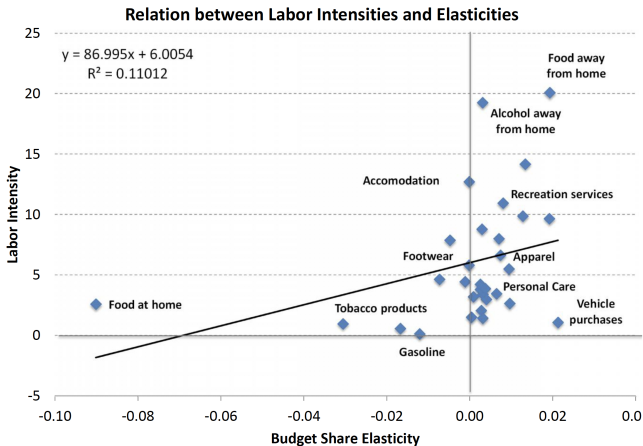
PPI and Compustat Matched Data

Table: Market shares and Labor Intensity: 2012

Industry	\$m Expenditure in 2012	Labor Intensity			Market share		
		Low	Middle	High	Low	Middle	High
31	956,083	0.40	3.41	n.a.	34%	66%	n.a.
32	1,461,253	2.69	2.85	4.59	27%	47%	26%
33	2,494,959	1.40	2.41	3.32	38%	57%	5%
Total	4,912,295	1.59	2.74	3.06	33%	54%	13%

- Employment fell 8.6%.
- In counterfactual without trading down only 3.9%.

Household Data: Elasticity of Budget Share WRT Expenditure vs. Labor Intensity



Evaluation

- Very interesting paper.
 - Took a lot of cleverness and work to get this data set together.
- Data limitation: Price as proxy for quality.
 - They do lots to show this is reasonable and to argue that they are not picking up cyclical price changes.
 - Still a concern, but best you can do given data.
- Is this a new phenomenon? Or common to all recessions?
 - Cannot tell given freshness of data.
 - Really about how good of a counterfactual the “no trading down” counterfactual is.
- What is driving all of this?