Discussion of “Income Dispersion and Counter-Cyclical Markups”
by Edmond and Veldkamp

Emi Nakamura
Federal Reserve Bank of NY, Columbia University, NBER

November 16, 2007
Contributions:

Facts

- Estimates from PSID suggest earnings dispersion is counter-cyclical (Storesletten et al., 2004)
- Several papers argue that markups are countercyclical
- Can cyclicality of earnings dispersion explain countercyclical markups?
- Novel, exciting link
should, on average, exhibit greater cross-sectional dispersion (as long as $\rho$ is large and $\sigma_\varepsilon > \sigma_\eta$). Figure 1b shows that this is a characteristic of our panel. The cohort coefficients $a_j$ are plotted against the fraction of years during the working life of each cohort that were contractions (defined as the National Income and Product Accounts measure of gross domestic product growth being below average for the elders of each cohort). Although there are a number of cohorts that worked through
Contributions:

Model (Simple Version)

- Continuum of agents
- $U = \log c_i + \theta (1 - n_i) + \nu \int_0^1 x_{ij} dj$
- Discrete choice: $x_{ij} = 0$ or $1$
- Wages: $w_i$ dist. unif[$z - \sigma, z + \sigma$]

Consumer follows threshold rule: Buys if $w_i \geq \theta/\nu p_j$
Contributions:

Model

Aggregate demand Curve:

\[ x(p_j) = \frac{z + \sigma}{2\sigma} - \frac{\theta/\nu}{2\sigma} p_j \]

Elasticity decreasing in:

- Productivity \( z \)
- Earnings dispersion \( \sigma \)
Figure 1: **Lowering price is more beneficial when dispersion is low.**

The shaded area represents the increase in the probability of trade from lowering the price, by an amount equal to the width of the shaded area. This higher probability, times the expected gains from trade, is the marginal benefit to reducing the price. Willingness to pay is based on agents’ earnings.

because some agents are more productive. By manipulating the idiosyncratic productivity distribution, we show that more dispersion results in higher markups and higher prices.

Theory alone cannot tell us if the variation in earnings dispersion is too small or insufficiently counter-cyclical to generate observed markups. Therefore section 2 calibrates and simulates a dynamic version of the model. Section 2.4 documents our main results: The model’s optimal markups are determined primarily by earnings dispersion. Since measured dispersion is counter-cyclical, markups are as well. This is consistent with empirical studies in both macroeconomics and industrial organization. The resulting prices look inflexible because they fluctuate less than marginal cost. Yet, there are no price-setting frictions.

The model explains markups without compromising its ability to match macroeconomic aggregates. Section 2.5 compares the model’s predictions for employment, real wages, and profits to their empirical counterparts. The model does reasonably well in capturing these aggregates. To keep heterogeneous income processes tractable, our model abstracts from important issues debated in the literature on income heterogeneity and welfare (Krusell and Smith (1998), Rios-Rull (1996) and Krueger and Perri (2005b)), such as capital accumulation or other consumption-savings behavior. Tractability comes at a cost: Omitting capital hurts
Contributions:

Key Predictions

1. Countercyclical earnings dispersion $\rightarrow$ Countercyclical markups
2. Procyclical productivity $\rightarrow$ Procyclical markups

Effect #1 more important

Quantitative calibration: Countercyclicality of markups, long-run trends in wages, agg. volatility

Empirical evidence: State-level panel data
My Comments

1. How general are the results?
   - Alternative Demand curves: Comparison to BLP

2. Empirical evidence
   A. Evidence on the cyclicality of earnings dispersion
   B. Panel data analysis
1. How general are the results?

**Alternative Demand Curves**
**Edmond + Veldkamp:**

- Consumers buy either one of zero units, expand consumption of $x_{ij}$ by buying more types
- More income dispersion $\rightarrow$ Less consumers “on the margin”
- Degenerate demand curve for indiv. consumer
- No effect on price of consumers “away from the margin”

**Empirical evidence:** Heterogeneous behavior conditional on income, multi-unit purchases
Figure 1: **Lowering price is more beneficial when dispersion is low.**
The shaded area represents the increase in the probability of trade from lowering the price, by an amount equal to the width of the shaded area. This higher probability, times the expected gains from trade, is the marginal benefit to reducing the price. Willingness to pay is based on agents’ earnings.

because some agents are more productive. By manipulating the idiosyncratic productivity distribution, we we show that more dispersion results in higher markups and higher prices.

Theory alone cannot tell us if the variation in earnings dispersion is too small or insufficiently counter-cyclical to generate observed markups. Therefore section 2 calibrates and simulates a dynamic version of the model. Section 2.4 documents our main results: The model’s optimal markups are determined primarily by earnings dispersion. Since measured dispersion is counter-cyclical, markups are as well. This is consistent with empirical studies in both macroeconomics and industrial organization. The resulting prices look inflexible because they fluctuate less than marginal cost. Yet, there are no price-setting frictions.

The model explains markups without compromising its ability to match macroeconomic aggregates. Section 2.5 compares the model’s predictions for employment, real wages, and profits to their empirical counterparts. The model does reasonably well in capturing these aggregates. To keep heterogeneous income processes tractable, our model abstracts from important issues debated in the literature on income heterogeneity and welfare (Krusell and Smith (1998), Rios-Rull (1996) and Krueger and Perri (2005b)), such as capital accumulation or other consumption-savings behavior. Tractability comes at a cost: Omitting capital hurts
Alternative Demand Curves (cont’d)

• Berry, Levinsohn and Pakes (1995)
• Consumer $i$ selects item with highest indirect utility
• $U_{ij} = \alpha_j - \beta_i p_j$
• Assume $\beta_i$ differs across consumers with different incomes
• No tractable analytical pricing formula

$$s_{ij} = \frac{\exp(\alpha_j - \beta_i p_j)}{1 + \sum_{k=1}^{K} \exp(\alpha_k - \beta_{ik} p_k)}$$
Alternative Demand Curves (cont’d)

• I simulated prices for the coffee market for two cases
  – Case 1: No dispersion in price elasticity (logit model)
  – Case 2: High income consumers (one std above mean) have price elasticity 25% higher than mean

• Results: Markups are not strictly increasing in income dispersion

• Model with greater dispersion can produce lower markups

Key difference: BLP model yields non-degenerate demand curves for individual consumers → Aggregate demand is integral over indiv. demand curves

Could also matter for effects of prod. shocks?
2. Empirical Evidence: A. Countercyclical Earnings Dispersion

Storesletten, Telmer and Yaron (2004): Dispersion is countercyclical

Related Facts:

1. Detrending is key: Recent “countercyclicality” due to rapid rise in dispersion in 1980’s

2. Most countercyclical movements come from lower half of income distribution
   – PSID oversamples low wage workers

3. Consumption dispersion much less countercyclical than earnings dispersion
   – Edmond+Veldkamp find results are stronger if use consump. dispersion: puzzling
Fig. 1.—Cross-sectional variance of earnings, based on the idiosyncratic component (\( \mu_v \) from eq. [2]) of log labor earnings plus transfers from the PSID, 1968–93. a, Cross-sectional variance by age. The variances control for “cohort effects” by regressing cohort age-specific cross-sectional variances on cohort age dummy variables as in Deaton and Paxson (1994) and Storesletten et al. (in press). The points in the graph are the age coefficients, rescaled to match the level of variance at age 40. b, Macroeconomic history vs. cross-sectional variance (cohorts). The panel plots the cohort coefficients from the dummy variable regression underlying panel a against the fraction of contractionary years during which the oldest members of that cohort were of working age. c, Macroeconomic history vs. cross-sectional variance. The panel plots the age-normalized cross-sectional variance of the persistent shock underlying eq. (5) against the fraction of contractionary years during which members of that age panel–year worked through. d, Cross-sectional moments by time. The panel reports the linearly detrended cross-sectional mean of log income (\( y^\mu \) from eq. [1]) and the linearly detrended standard deviation of \( u_v \), pooled across all ages, for each year 1968–93. The standard deviation is additively scaled for graphical reasons. The correlation coefficient between the two series is \( -0.74 \). Panel d is robust to (i) alternative methods of detrending the mean and (ii) using the coefficient of variation instead of the standard deviation. Further details are given in Sec. III.

should, on average, exhibit greater cross-sectional dispersion (as long as \( \rho \) is large and \( \sigma_c > \sigma_p \)). Figure 1b shows that this is a characteristic of our panel. The cohort coefficients \( a_t \) are plotted against the fraction of years during the working life of each cohort that were contractions (defined as the National Income and Product Accounts measure of gross domestic product growth being below average for the elders of each cohort). Although there are a number of cohorts that worked through
Figure 3. 90/10 Weekly and Hourly Wage Inequality in May/ORG and March CPS Series, 1963 - 2003
Figure 5. 50/10 Full-Time Weekly and Hourly Wage Inequality in May/ORG and March CPS Series, 1963 - 2003
Figure 4. 90/50 Full Time Weekly and Hourly Wage Inequality in May/ORG and March CPS Series, 1963 - 2003
In summary, much of what we can infer graphically appears robust to the inclusion of information that is not represented in the graph. In particular, the age pattern in the cross-sectional variances (fig. 1a) suggests near–unit root behavior, and this is robust to the inclusion of autocovariances, the moments typically used to identify persistence.

A. Consumption Data

To this point we have focused on labor earnings. For many questions, most notably asset pricing, we are equally interested in consumption and how its cross-sectional distribution is related to aggregate variation. Figure 2 displays plots analogous to those in figure 1 using data on food expenditure from the PSID (the only consumption data available). Using these consumption data, table 3 replicates the estimation in table 2. Many of the patterns displayed in figure 1 for earnings seem to also appear for consumption. Figure 2a displays an almost linear rise in
2. Empirical Evidence

B. Panel data analysis

Edmond + Veldkamp:

- Sort data into groups based on earnings dispersion across counties within states
- Compare “markups” (inv. of real wage) across groups

Similar to panel regression:

$$-\log(w_{ij}) = \alpha + \beta \log(\sigma_{ij}) + \gamma \log(y_{ij}) + I(\text{year})$$

$w_{ij}$: Real wage, inverse gives markup; $\sigma_{ij}$: Earnings dispersion; $y_{ij}$: Per-capita real gdp

Regression results: Estimate $\beta = 0.03$ positive and significant

Note: All identification comes from cross-sectional differences in markups and income dispersion
B. Panel data analysis (cont’d)

- State-level price indexes not widely available

Concerns:

1. Prices in all states normalized to one in 1990, dispersion set to zero

   Arbitrary normalization $\rightarrow$ Cross-sectional comparisons not meaningful

2. Drop all data after 1997 due to switch from SIC to NAICS (Is this really necessary?)
State Price Levels: Edmund-Veldkamp
Normalization 1990=1 (Diff. vs. California)
State Price Levels: Alternative Normalization
1969=1 (Diff. vs. California)
B. Panel data analysis (cont’d)

- Data is on changes (not levels) of prices in different states
- Alternative normalizations yield different results → Smaller $\beta$

Potential Alternatives:

1. Difference in Difference regression:

$$- \log(w_{ij}) = \alpha + \beta \log(\sigma_{ij}) + \gamma \log(y_{ij}) + I(\text{year}) + I(\text{state})$$

→ Implies $\beta = -0.03$ rather than $\beta = 0.03$

2. Collect meaningful data on relative prices
B. Panel data analysis (cont’d)

Switch from SIC to NAICS in 1997 affects construction of state-level GDP → Edmond+Veldkamp drop data after 1997

Question: Why would change invalidate state-level GDP data in recent period?

Potential concern:

- Could introduce bias: Correlations appear diff. after 1990
Markup vs. Dispersion in 1969
Conclusion

New, exciting link between income dispersion and markups

Theory

How general is relationship between earnings dispersion and markups?

- Alternative demand specifications yield embarrassment of riches
- → Wide range of markup behavior
- Does relationship between earnings disp. + markups depend on particular specification of demand?
  - E+V assume degenerate demand curve for indiv. consumers
  - BLP (1995) seems to imply diff. results

Small point on numerical simulation: Quantitative simulations should be for entire economy (not just x-sector), since switching between x and c sectors affects markups
Conclusion (cont’d)

Evidence

Evidence on cross-sectional earnings dispersion

- Most increase in dispersion for lower half of earnings dist: Can this be used to yield tighter empirical predictions?
- Why don’t results change using consumption dispersion (little cyclicality)?

Evidence from state-level panel

- Panel data analysis results depend on arbitrary normalization of relative prices in 1990’s (affects markup measures) → Very hard to interpret

- Need state-level fixed effects or meaningful data on relative price levels → Could change results