

Preamble

Becoming a Successful Researcher

1. Energy, Time, Smarts, Ambition, Perseverance,
Instructors, Fellow Students,...

2. Tools and Skills

- Math tools (e.g., dynamic optimization)
- Numerical analysis techniques
- Constructing and analyzing economic models
- Statistics and Econometrics – theory and methods
- **Data sources, data handling skills, measurement
- **Empirical designs
- *Using statistics and econometrics in research
- **Communication skills – oral and written

3. **Knowledge of the field in course-related topics:

- To build on what came before
- To advance the frontier rather than reinvent the wheel
- For inspiration, and for examples of how (not) to do research
- To connect with other researchers, and to persuade them that your work is interesting and worthy of their attention

4. **How to develop good ideas for (empirical) research, and how to devise an effective research strategy: new, feasible and with high potential to cast light on important topics, questions and models

5. **Critical Judgment

- Assessing strengths and weaknesses in work by others and yourself
- Identifying & dropping weak or impractical research ideas
- Refining and pursuing promising/good research ideas

For the most part, this course focuses on applying tools and techniques you've learned elsewhere in your studies. Two partial exceptions:

1. You will learn some basic text-based methods, apply (some of) them in the homework assignments and see several examples of text-based methods in economics research. Examples include:
 - Marco Sammon's tutorial, An Introduction to Python for Text Analysis.
 - Homework Assignments 1 and 2, which ask you to construct text-based measures of risk exposures from 10-K filings and use them in research that casts light on firm-level equity returns and other outcomes.
 - “Measuring Economic Policy Uncertainty,” my paper with Baker and Bloom that uses scaled frequency counts of newspaper articles to quantify policy-related uncertainty and assess its effects on firm-level and aggregate performance.
 - Special lecture by Tarek Hassan: He applies machine-learning methods to transcripts of conference calls about quarterly earnings reports for publicly listed firms. He uses these methods to quantify firm-level policy risks and assess effects on investment, hiring, lobbying and more.

The use of text as data and text-based methods in economics research is exploding rapidly. See the recent and excellent survey of “Text as Data” in economics research by Gentzkow, Kelly and Taddy (2017). For more on machine-learning methods applied to textual data, you might start by perusing the materials and references on Matt Taddy’s website: <http://taddylab.com>.

2. You will have ample opportunity to practice your oral and written communication skills in this course.

- Most PhD students in Economics invest too little in developing and polishing their communication skills, in my view.
- If you can’t express your ideas clearly, it’s a sign you haven’t thought hard enough about your ideas and how to explain them to others.
- Poor communication skills slow your intellectual development. If you can’t express your ideas clearly, it’s hard for others to provide useful feedback.
- For the same reason, you will make faster progress on your dissertation and your job market paper if you write and speak clearly.
- See the course syllabus for more on the importance of communication.
- Get *Strunk & White’s The Elements of Style*. Read it. Practice its principles and rules.
- Read “An Economist’s Guide to Visualizing Data,” by Schwabish in the *J. of Economic Perspectives*, 28, no 1. Apply its lessons and principles.

Longitudinal Business Databases: A Research Tool for Economists

- Governments routinely collect data on the employment, wages, revenues, industry and location of nearly all businesses, often at both the establishment and firm levels.
 - Data include taxpayer IDs and other identifiers
- Governments use these data for tax compliance purposes, as inputs to NIPA tables, as sampling frames for business surveys, and as raw material in the creation of widely used economic statistics.

Large Business Databases

- With (much!) work, these raw data can be turned into core longitudinal research databases covering the universe of business firms and establishments
 - Establishments linked to parent firms
 - Both followed longitudinally (harder for firms)
 - In some cases, employers are also linked to their employees, and both are followed longitudinally.
 - In some cases, businesses are also linked to their owners, and both are followed longitudinally.

Large Business Databases, 2

- Data from other sources – one-off and recurring surveys, other administrative records, and proprietary data – are often merged with these core databases to investigate a specific issue.
- Advances in data storage and computing power greatly increase the scope for building these databases and using them as research tools.
- The next slide lists two core longitudinal U.S. business databases that emerge from different administrative record systems.

Two Large U.S. Databases

1. LBD: Longitudinal Business Database (Census)
 - Firms & Establishments, linked and tracked over time
 - Universal coverage, annual observations since 1976
 - Core variables: employment, payroll, sales/revenue (since 1994), industry, location, company name, IDs
2. BED: Business Employment Dynamics (BLS)
 - Firms (intra-state) & Establishments, linked and tracked over time
 - Universal coverage, quarterly since 1990
 - Core variables: employment, industry, location, IDs

The LBD and BED cover businesses with 1+ employees⁸

Other Business Databases

- Other longitudinal business databases derive from panel surveys conducted by statistical agencies, proprietary sources created for commercial purposes, etc.
- Some of the most exciting research ideas on the margin combine core business micro datasets like the LBD and BED with smaller, targeted sources that contain rich information about particular aspects of business behavior and outcomes.

Selected Business Databases

3. COMPUSTAT: Rich source of data on firms listed on major exchanges or traded OTC.
 - Heavily used in economics and finance research.
 - Considered in more detail later in this lecture
 - You will use in Homework Assignments #1 and #2
4. 10-K filings: Text documents that publicly listed firms file with the U.S. Securities & Exchange Commission:
 - Available for download through EDGAR.
 - You will use 10-K filings for text-based analysis in HWs 1&2.

5. LRD: A large, rotating panel of manufacturing plants with annual coverage back to 1972 and coverage in business census years before then

- Large, rich set of measures
- Draws on Annual Survey of Manufactures and once-every-five years Census of Manufactures
- Heavily exploited in economics research, e.g., my book on *Job Creation and Destruction*.

6. Manufacturing Energy Consumption Survey

- Highly detailed data on energy-related inputs, expenditures, technologies and practices for roughly 15,000 manufacturing plants
- Every 3 or 4 years since 1985
- See Davis et al. (RESTAT, October 2013) for info.

7. Annual Surveys of Business for Retail, Wholesale and Manufacturing (ASM).
8. Manufacturing & Organizations Practice Survey (MOPS) – a supplement to the ASM.
 - Several papers in Sections II and VIII of the reading list.
 - I am deeply involved in designing the part of MOPS that deals with eliciting subjective probability distributions over future plant-level outcomes

9. Various Censuses of Business

- Extensive coverage of establishments and firms about once every five years, large set of measures
- Coverage of Construction, FIRE, Retail, Wholesale, Manufacturing, Mining, Services and more. Only the Manufacturing data have been heavily worked.
- First available year varies by industry sector

10. ILBD: LBD + revenue, industry and ownership for businesses with no employees. (Davis et al, 2009).
11. Job Openings and Labor Turnover Survey (JOLTS): BLS establishment-level survey of job vacancies and worker flows (quits, layoffs, hires, etc.)
12. CapitalIQ: Commercial platform, extensive data on financial characteristics of businesses and their sale (changes in ownership, capital structure, etc.)
www.capitaliq.com/Main3/ourproducts_platform.asp
13. Dealogic: Another commercial platform with data on financial characteristics of businesses, business sales, etc. www.dealogic.com/

- Datasets 1 and 5-10 are products of the U.S. Census Bureau. They share common business identifiers, making it relatively easy to merge the establishment-level and firm-level data across databases. To get a fuller sense of the range of business micro data sets that reside within the U.S. Census system, peruse

www.census.gov/ces/dataproducts/economicdata.html

- Likewise, datasets 2 and 11 are products of the U.S. Bureau of Labor Statistics, and it is reasonably straightforward to merge them.

- When business datasets do not share common identifiers, they can be merged on the basis of business name and address, industry, size and other characteristics. This type of merging process can involve a great deal of work, and it typically yields match rates across datasets well below 100 percent.
- Fortunately, you can often build on previous efforts by others. For example, Davis et al. (2007) build on McCue and Jarmin (2005) to match Compustat data to firm-level records in the LBD through 2005.

Selected Longitudinal Employer-Worker Datasets

14. Longitudinal Employer Household Dynamics
 - LEHD micro data: quarterly earnings for workers, linked to employers and both followed longitudinally.
 - Data start in 1990 for selected states, with more states available in more recent years
 - See www.census.gov/ces/dataproducts/lehddata.html
15. Social Security Administration (SSA) longitudinal employer worker data
 - Annual longitudinal data on the earnings of private sector employees from 1974 onwards, linked to employers who are also followed longitudinally

Selected Longitudinal Employer-Worker Datasets

16. German Social Security Data – Similar to LEHD and U.S. SSA data, but better in two respects: First, they allow for a relatively clean distinction between earnings and wages. Second, they allow for a much sharper dating of job-loss events and other employment transitions.

Strong recent applications include:

- Jarosch (2015) in an analysis of the earnings losses of displaced workers.
 - Jarosch graduated from Chicago, and this was his job market paper. It's now R&R at *Econometrica*!
 - His paper has its roots in work he did for this course!

What Can You Do with These Datasets?

A. New measurement that informs our thinking about fundamental aspects of economic behavior.

Examples:

1. Davis and Haltiwanger (1992) and the book by Davis, Haltiwanger and Schuh (1996) develop empirical underpinnings for the flow approach to labor markets.
Slide 20 and Section III in the course reading list.
2. In “Volatility and Dispersion in Business Growth Rates,” Davis et al. (2007) show that trends in business volatility differed drastically between publicly listed and privately held firms in the decades leading up to 2001.
Covered later in this lecture.

3. Davis and Haltiwanger (2014) document a secular fall in the “fluidity” of U.S. labor markets and develop evidence on its implications for employment. **Later in the course.**
4. “Firming up Inequality” by Song et al. (2016) exploits longitudinal worker-employer linked data from the SSA to cast new light on the evolution of U.S. earnings inequality.
5. “Capitalists in the 21st Century” by Smith, Yagan and Zidar (2017) exploits longitudinal firm-owner linked data to debunk the notion that passive rentiers have replaced the working rich at the top of the U.S. income distribution.

Empirical Regularities Uncovered by the Flow Approach to Labor Markets

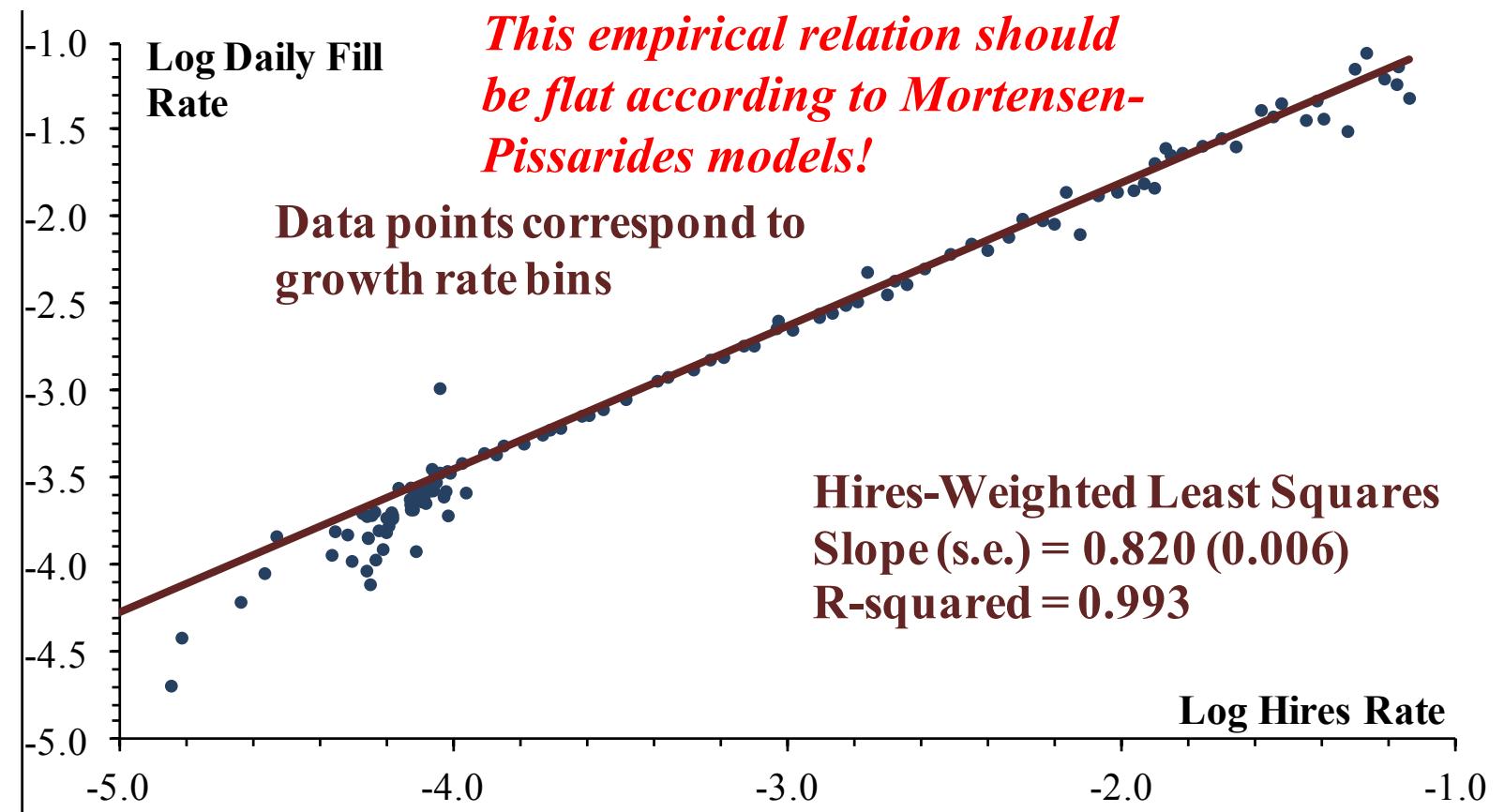
- Gross job flows across employers are remarkably large – in good economic times and bad, in every market economy, in virtually every industry and sector
- Worker flows are larger yet
- Between-sector employment shifts account for a small share of job flows. Idiosyncratic factors predominate.
- Job and worker flows exhibit pronounced cyclical movements.
- Worker and job flows are tightly linked in the cross section and over time. (Davis, Faberman and Haltiwanger, 2012, J. of Monetary Economics).
- All students of this course should read Davis, Faberman and Haltiwanger (2006). That will give you the minimal background you need. If you want to dig deeper, see the readings in Section III.

B. Uncovering empirical regularities that challenge standard theory and guide new research.

Example: Davis, Faberman and Haltiwanger (2013) use JOLTS micro data to study vacancies, hires and vacancy yields in a large sample of U.S. employers.

- They show that the C-S behavior of vacancy yields is inconsistent with standard equilibrium search theories.
- They develop compelling evidence that employers use other instruments, in addition to vacancy numbers, to vary their pace of hiring.
- Their evidence leads them to formulate a generalized matching function that accommodates a role for recruiting intensity (per vacancy) and outperforms the standard matching function, $H=M(U,V)$, in many ways.²¹

Vacancy Fill Rate and Gross Hires Rate



Note: The figure plots the relationship of the log daily job-filling rate to the log gross hires rate across growth rate bins in [-.3, .3] and the hires-weighted least squares regression fit of the bin-level data. Bin-level fill rates estimated from establishment-level data sorted into bins after removing mean establishment growth rates.

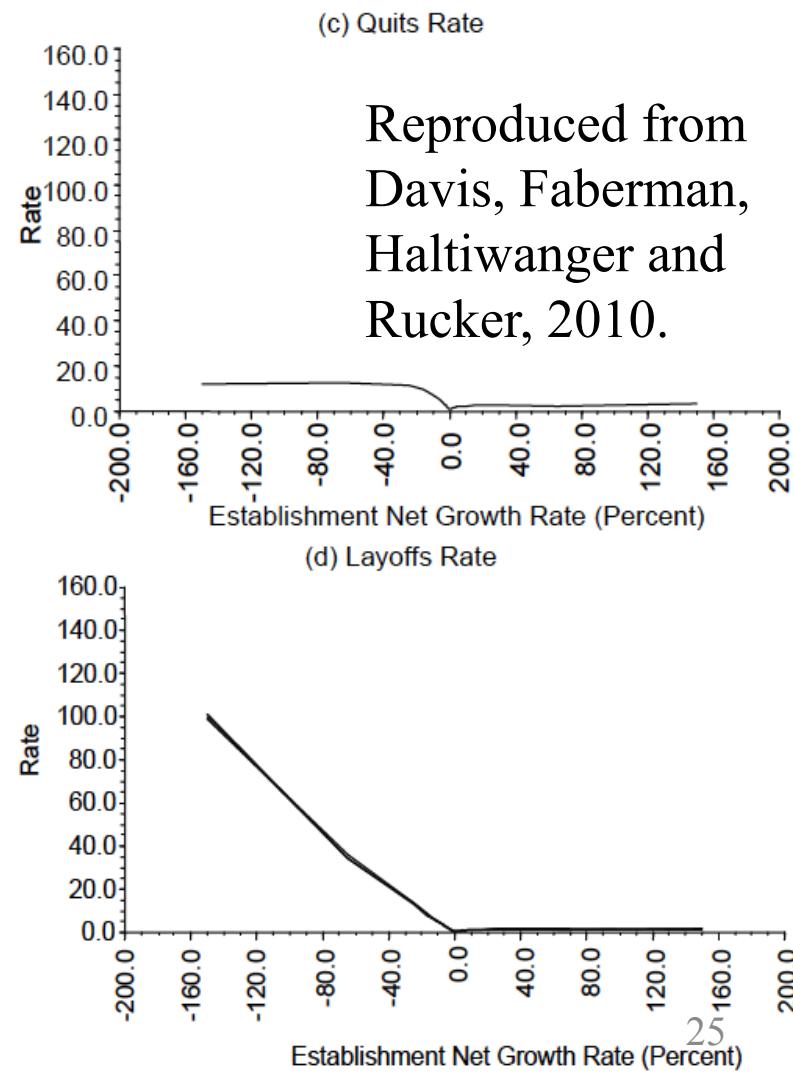
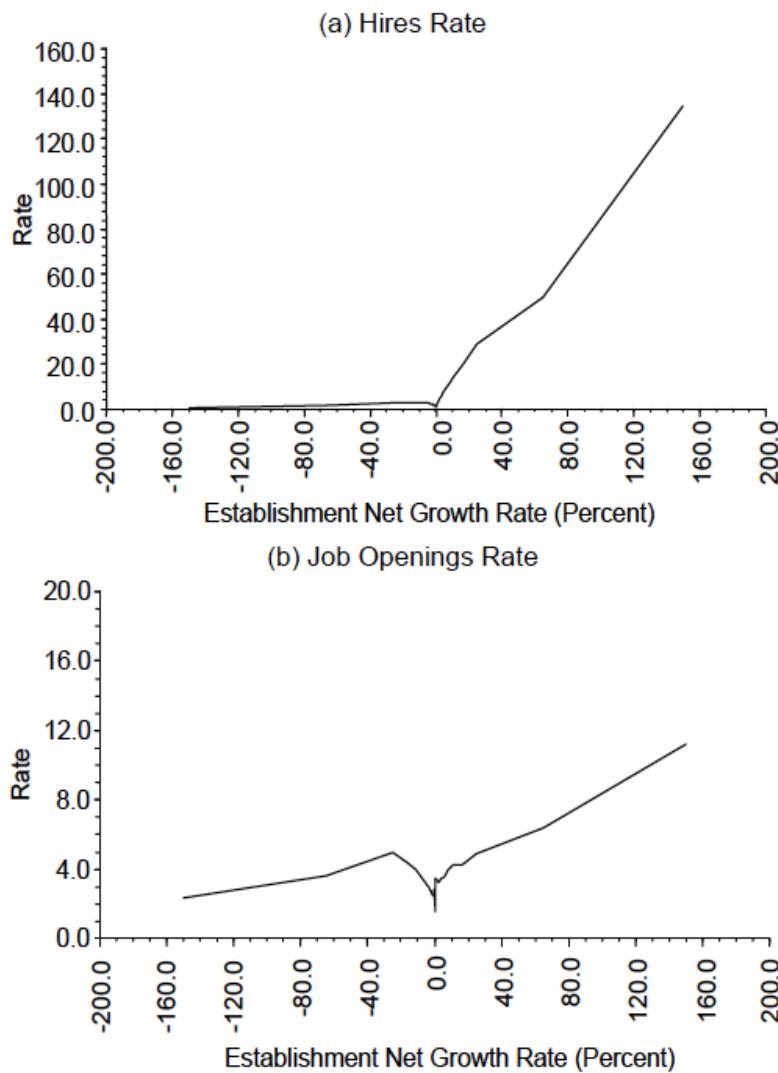
- We will cover this paper on “The Establishment-Level Behavior on Vacancies and Hiring” in detail **later in the course**.
- See **Section VI** in the course reading list for related empirical studies and several papers that advance theoretical explanations for the empirical relationship on the previous slide and other evidence in the paper.
- We will also consider some work-in-progress that exploits proprietary data that links millions of jobseekers, applications and vacancy postings.

C. Identifying and correcting sample design flaws to produce better aggregate statistics.

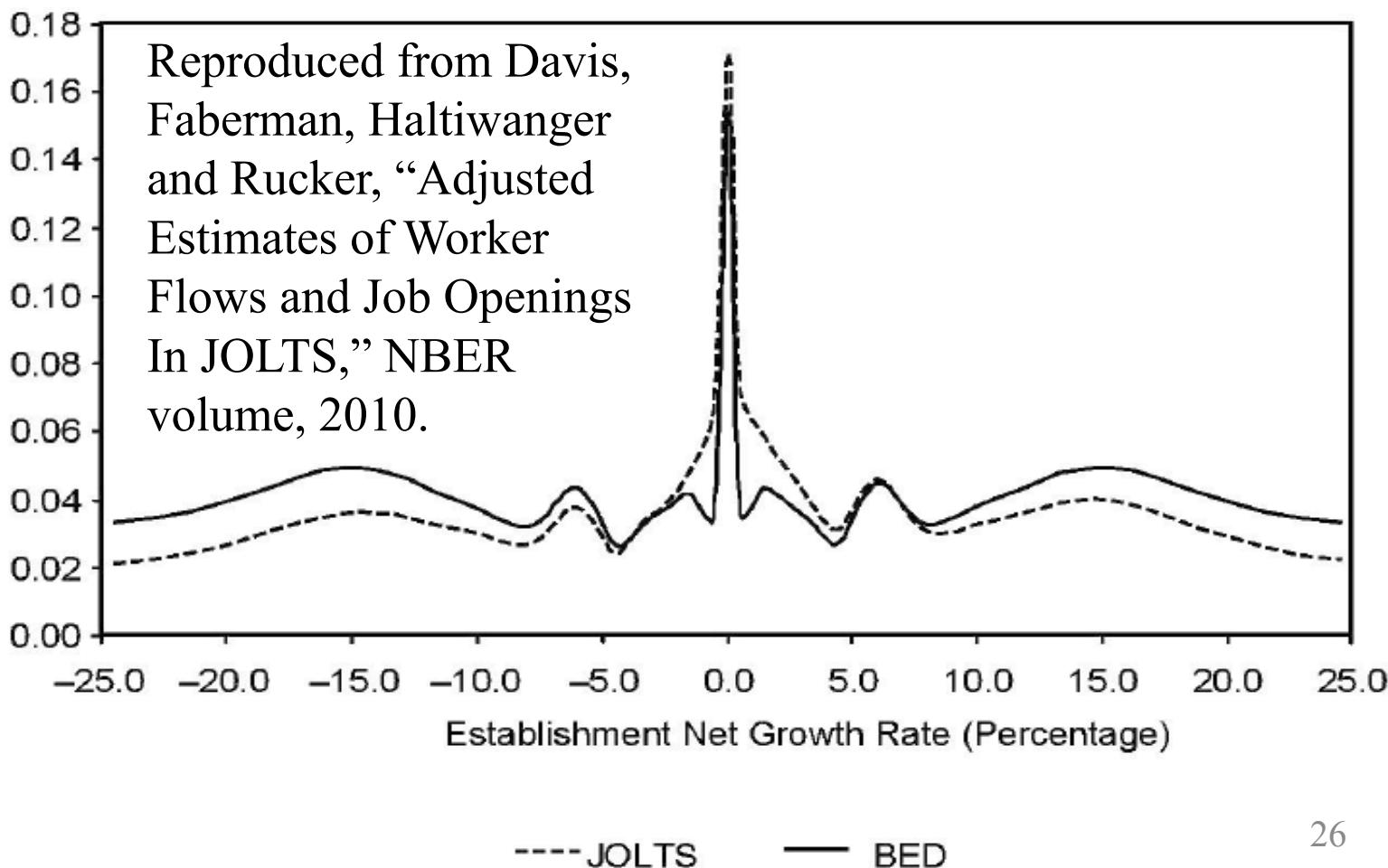
Subtle flaws in sample design can lead to major errors in measurement and inference.

- Remark: A sample design suitable for estimating levels can be unsuitable for estimating changes or flows.
- Example: The original sample design for the Job Openings and Labor Turnover Survey (JOLTS) under weighted tail mass in the cross-sectional growth rate density. As a result, published JOLTS statistics understated worker flows and job openings, and misstated the relative cyclicalities of hires vs. separations and quits vs. layoffs
- Solution: Reweight the sample to ensure that it replicates the employment growth rate density in the BED.

Rates of Hires, Quits, Layoffs and Job Openings in the Cross Section of Establishment Growth Rates, JOLTS Micro Data, 2001-2006



Cross-Sectional Densities of Establishment Growth Rates (Employment Weighted)



- Our adjusted statistics for hires and separations exceed the published statistics by about one third.
- Our adjusted layoff rate is more than 60 percent greater than the published layoff rate.
- Our adjustments significantly alter time-series properties as well.
 - Aggregate hires are 50 percent more variable than separations in (old) published JOLTS statistics, as measured by the variance of quarterly rates, but 20 percent less variable according to our adjusted statistics.
 - Quarterly quit rates are more than twice as variable as layoffs in the (old) published statistics but equally variable according to our adjusted statistics.

- BLS revised its published JOLTS statistics after we circulated our paper. Their new statistics are much closer to our “adjusted estimates”.
- Do other important economic statistics suffer from similar measurement problems that distort estimated levels and time-series properties?
 - Investment expenditures, business borrowing?
- Perhaps, but it’s unclear (to me).
 - The errors introduced by flawed and ill-suited sample designs can be corrected ex post by adjusting survey-based estimates to match benchmark quantities.
 - However, suitable benchmarks are not always available or, when available, not always used well.

- For a very short and easy-to-digest discussion of the weaknesses in the JOLTS sample design, why they led to serious problems in the published JOLTS statistics, and how to correct for the sample design problems, read Davis (2010).
- While the basic idea behind the correction is quite simple, various challenges complicate the actual implementation. For the gory details, see Davis, Faberman, Haltiwanger and Rucker (2010).

D. Exploiting Cross-Sectional Relations to Construct Synthetic Time-Series Data

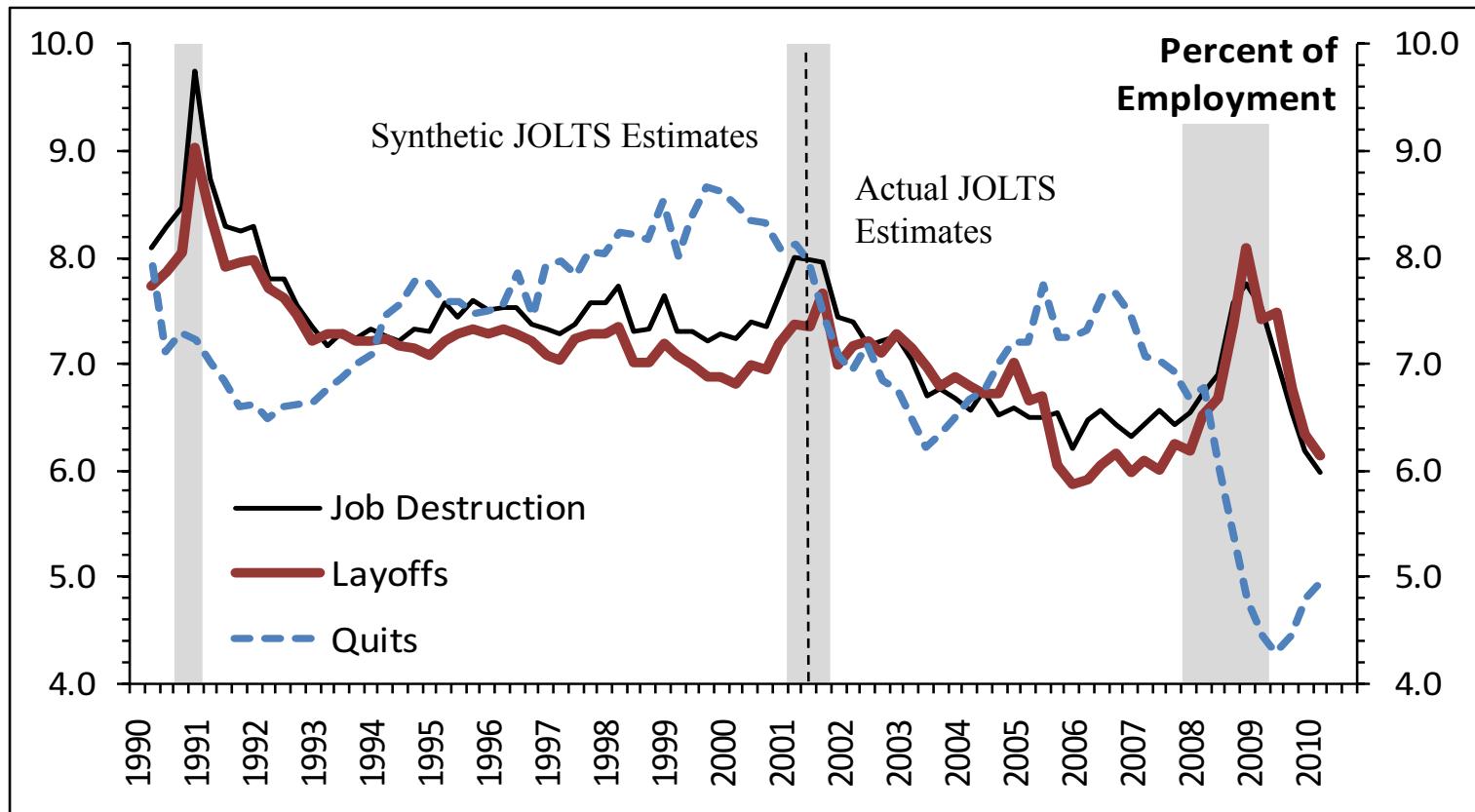
- Statistical model of cross-sectional relations + complete quarterly data on the cross-sectional distribution of establishment-level growth rates → synthetic data for aggregate worker flows

$$\hat{W}_t = \sum_g f_t(g) \hat{w}_t(g)$$

- BED data on f + model-based \hat{w} for 1990-2001
- BED data on f + JOLTS-based w for 2001-2010.

This method requires a good statistical model of how w (worker flow rate) relates to g (employment growth rate) in the cross section! See Davis, Faberman and Haltiwanger (J. of Monetary Economics, 2012) for details.

Quit, Layoff, and Job Destruction Rates



Layoffs move with job destruction. Quits move opposite to both.

This chart is reproduced from “Labor Market Flows in the Cross Section and Over Time,” by Davis, Faberman and Haltiwanger, *Journal of Monetary Economics*, January 2012.

E. Combining quasi-experimental variation and longitudinal business data to test theoretical predictions and estimate response magnitudes.

There are increasingly many examples of this sort, and they differ widely in character. This approach requires some ingenuity in recognizing a useful quasi experiment and in gathering or constructing data to merge into existing longitudinal business databases. If estimation of causal effects is the goal, then success also turns partly on whether the identification strategy is persuasive and yields enough power to recover reasonably precise estimates of the effects of interest.

Examples

- Estimating the effects of private equity buyouts on employment, job reallocation, productivity and compensation per worker.
 - Davis et al. (2014) advance the literature on the effects of PE buyouts in several respects, but perhaps their most important innovation involves the simultaneous use of firm *and* establishment data to estimate within-firm reallocation effects. **Covered in next lecture.**
- Identifying and quantifying spatial spillovers on the productivity of manufacturing plants.
 - Greenstone et al. (2010) compare outcomes at incumbent plants in counties that won contests for the opening of major new plants to outcomes in counties that lost. ³³

- Greenstone, List and Syverson (2012) estimate the effects of air quality regulations on TFP at U.S. manufacturing plants. Their quasi-experimental variation: air quality regulations are more stringent in some counties (and for some types of plants) than others.
- How large were the employment effects of credit market disruptions in the wake of the Lehman bankruptcy?
 - Chodorow-Reich (2014) investigates this question using differences in lender health after the Lehman crisis as a source of variation in the availability of credit to borrowers. Another very successful JMP[†]!

- How do shocks to investment opportunities at one plant affect investment outcomes at ***other plants in the same firm***? Does the answer turn on whether the firm is financially constrained?
 - Giroud and Mueller (2015) address these questions. They use the LRD to measure productivity, ownership, plant location, etc.
 - They use new airline routes that reduce travel time between the firm's HQ and certain of its plants to obtain exogenous variation in plant-level investment opportunities. “[A] reduction in travel time makes it easier for HQ to monitor a plant, give advice, share knowledge, etc., raising the plant’s marginal productivity thus making investment in the (treated) plant more appealing.”
 - Clever recognition of an interesting, non-obvious quasi-experiment in the data.

- How sensitive is state-level employment to state-level taxes on business income? How much of the employment loss in one state (in response to a hike in its tax rate on business income) is offset by employment gains in other states?
- Giroud and Rauh (2017) address these questions In “State Taxation and the Reallocation of Business Activity: Evidence from Establishment-Level Data,” using the LBD and focusing on firms that operate in multiple states.
- They marshal and exploit much knowledge of business taxation and the nature of variation in business tax rates across states, time and form of business organizations. They use this knowledge to isolate several sources of state-specific time variation in the effective tax rate on corporate income (for businesses organized as “C” corporations) and in the personal tax rate (for unincorporated enterprises and businesses organized as pass-through entities)³⁶.

F. Applications of employer-worker and business-owner linked longitudinal datasets.

Examples include items 4 and 5 on Slide 19 above.

Perhaps the leading applications of longitudinal employer-worker linked datasets involve the study of earnings losses associated with job displacement.

Jacobson, Lalonde and Sullivan (1993) provide an early and influential study that exploited employer-worker datasets and applied empirical techniques previously developed in research on program evaluation. More recent studies in the same mold include Couch and Placzek (2010), Von Wachter, Song and Manchester (2009), and Davis and von Wachter (2011).

Davis and von Wachter (DvW) also show that workhorse search and matching models fail to explain the size and cyclicity of the present value earnings losses associated with job loss. Observed losses are several times larger than predicted by standard theory. Recent papers by Dopelt (2016), Jung and Kuhn (2016), Krolkowski (2017), Huckfeldt (2016), and Jarosch (2015) consider various modifications to search and matching models to address this issue. We will cover the DvW paper carefully and discuss some of the related literature **later in the course**.

Volatility and Dispersion in Business Growth Rates: Publicly Traded Versus Privately Held Firms

NBER Macroeconomics Annual, 2006

By Steven J. Davis, John Haltiwanger,
Ron Jarmin and Javier Miranda

Background and Motivation

Start with some background and motivation to explain why we chose to work on this topic:

- A Puzzle: Two prominent parallel literatures had produced seemingly contradictory evidence.
- The facts at issue are relevant for important theories of reallocation and growth, frictional unemployment, and effects of risk sharing, input variety and competition on producer volatility.
- Compared to previous work on trends in business volatility, we had better data sources and a better empirical strategy for establishing the facts.

Alternative views of trends in firm level volatility and dispersion (Circa 2006)

- Rising volatility of growth rates in sales and employment among publicly traded firms
 - Comin and Mulani (2003), Comin and Philippon (2005)
- Rising variance in the idiosyncratic component of firm-level equity returns
 - Campbell et al. (2001), Fama and French (2004), many others
- Declining excess job reallocation rates and declining rates of business entry and exit
 - Davis, Faberman and Haltiwanger (2006), Faberman (2006), Jarmin, Klimek and Miranda (2003, 2005), and Foster (2003)

For the full references, see “Volatility and Dispersion in Business Growth Rates.”

Rolling Volatility of Business-Level Growth Rates, Fixed Window Length

$$\gamma_{it} = \frac{x_{it} - x_{it-1}}{(x_{it} + x_{it-1})/2}$$

$$\sigma_{it} = \left[\frac{1}{10} \sum_{\tau=-4}^5 (\gamma_{i,t+\tau} - \bar{\gamma}_{it})^2 \right]^{1/2}$$

Figure 1(a): Volatility, Publicly Traded Firms

Based on COMPUSTAT Data

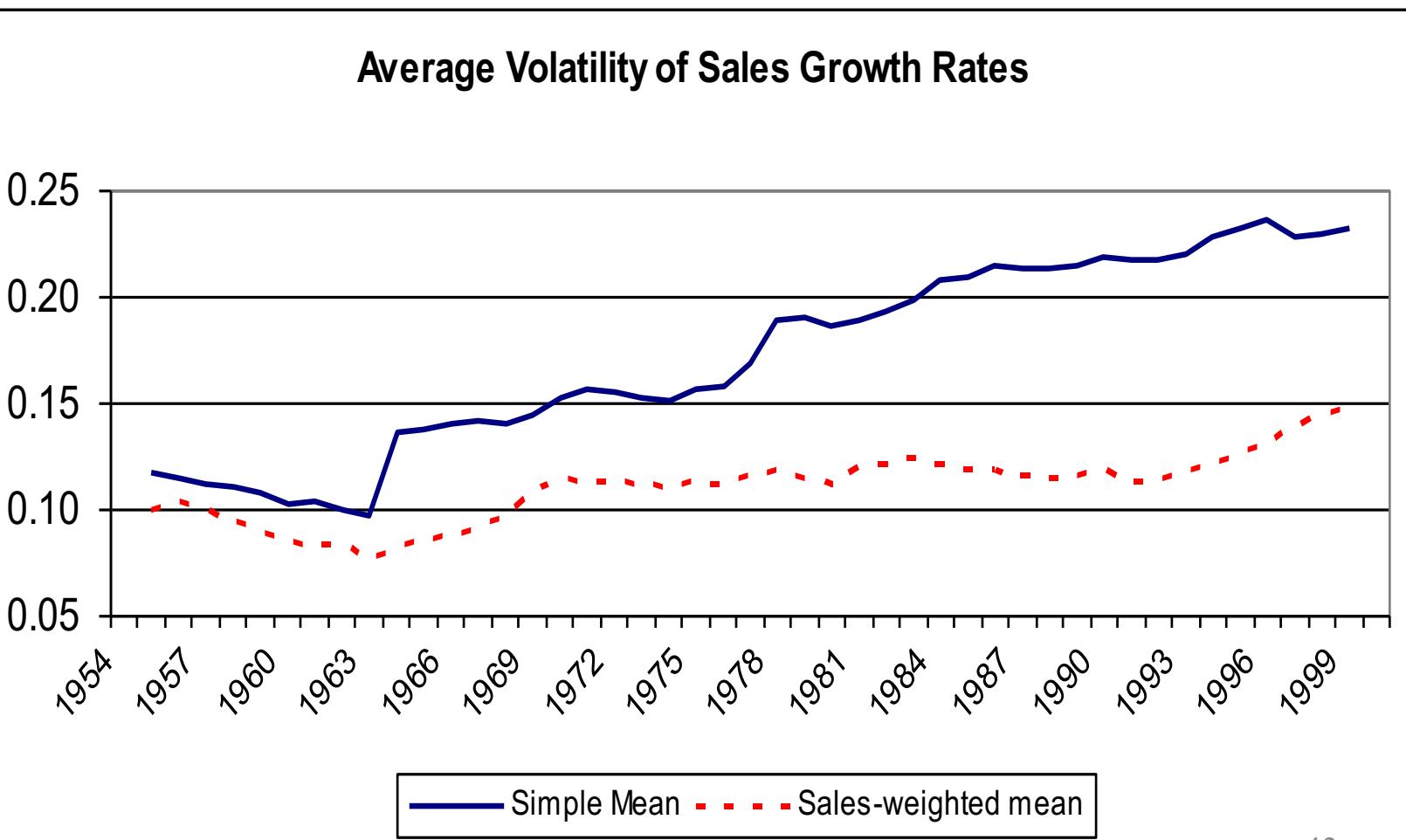


Figure 1(b): Volatility, Publicly Traded Firms

Based on COMPUSTAT Data

Average Volatility of Employment Growth Rates

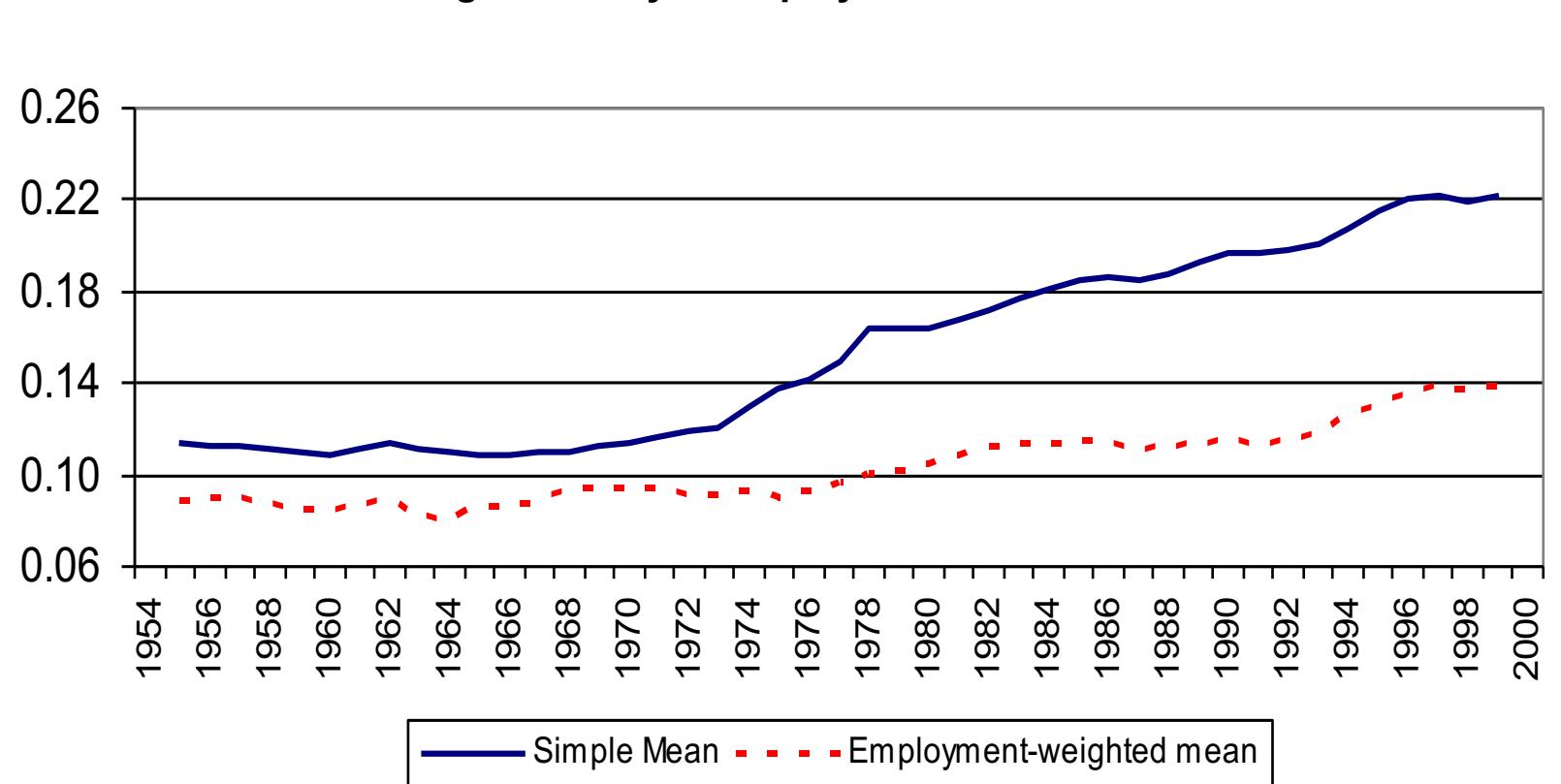
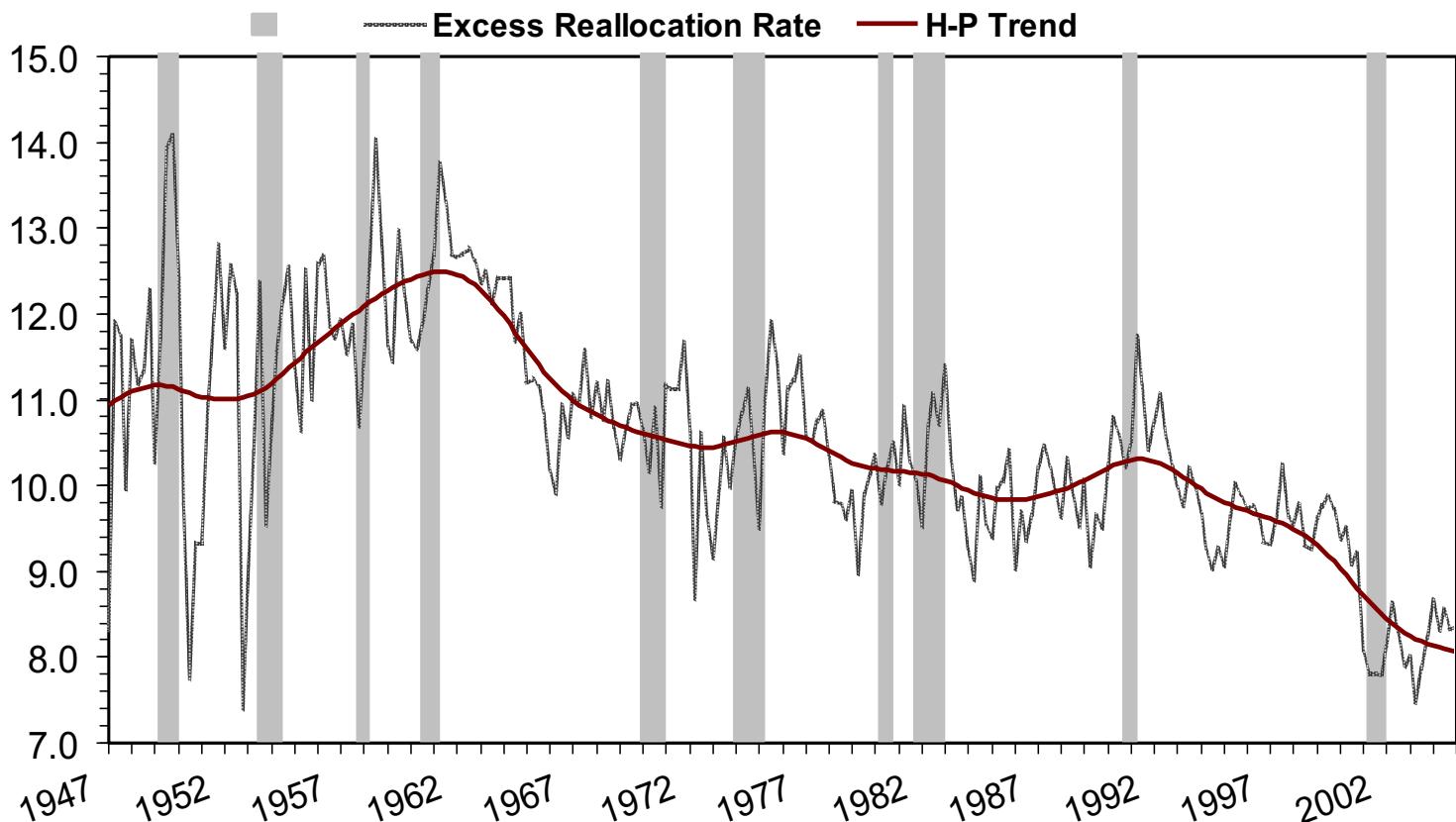
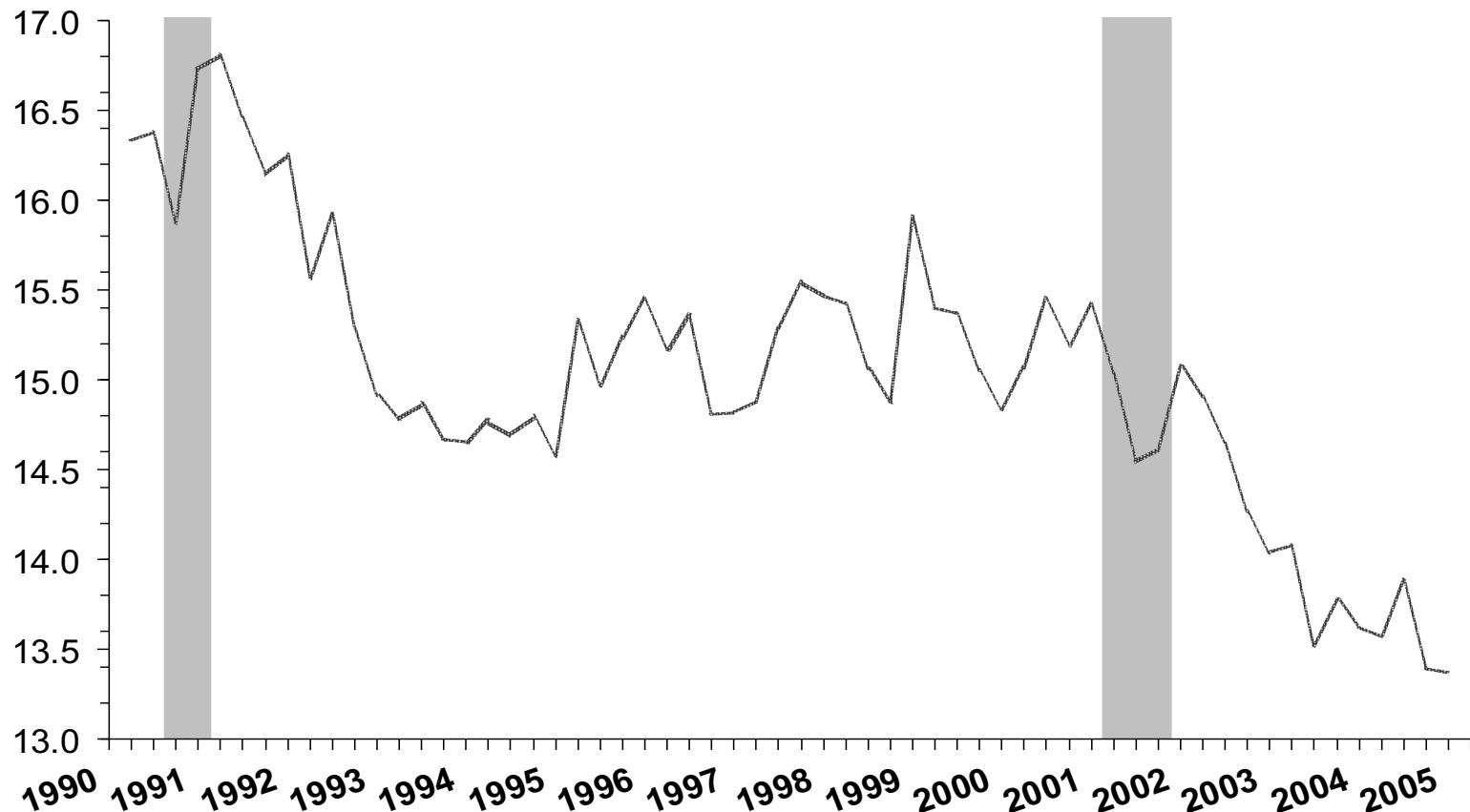


Figure 2a: Excess Job Reallocation, Manufacturing, Quarterly Rates, 1947 - 2005



LRD data spliced to other sources.

Figure 2b: Excess Job Reallocation, Private Business, Quarterly Rates



Based on data from the BLS Business Employment Dynamics 46

Why do we care?

- **Reallocation and growth**
 - Schumpeterian theories (Aghion-Howitt, 1998, Caballero, 2006, many others)
 - Industry-level productivity studies (FKH, 2001, etc.)
- **Theories of frictional unemployment (MP, etc.)**
- **Effects of diversification opportunities on risk taking, investment, growth (Obstfeld, 1994, etc.)**
- **Declining aggregate volatility and its connection to business-level volatility**
 - Financial market development (Thesmar-Thoenig, 2004, Acemoglu, 2005)
 - Greater competition in goods markets (Philippon, 2003, Comin and Philippon, 2005, Comin and Mulani, 2006)
 - Expanding input variety (Koren and Tenreyo, 2006)

A Simple Reason to Anticipate that Aggregate and Business-Level Volatility Measures Trend in the Same Direction:

Write the growth rate of firm i as a linear function of k mutually uncorrelated common shocks and an idiosyncratic shock:

$$\gamma_{it} = \sum_{k=1}^K \beta_{ik} Z_{kt} + \varepsilon_{it}, \quad i = 1, 2, \dots, N.$$

$$\text{Agg. Growth Rate} = \sum_{i=1}^n \alpha_{it} \gamma_{it},$$

where α_i is firm i 's share of activity

Then we can write the weighted mean of the firm-level growth rate volatility as:

$$\text{Firm Volatility} = \sum_{i=1}^n \alpha_{it} \sigma_{\varepsilon t}^2 + \sum_{i=1}^n \alpha_{it} \left[\sum_{k=1}^K \beta_{ik}^2 \sigma_{kt}^2 \right]$$

And the volatility of the aggregate growth rate as:

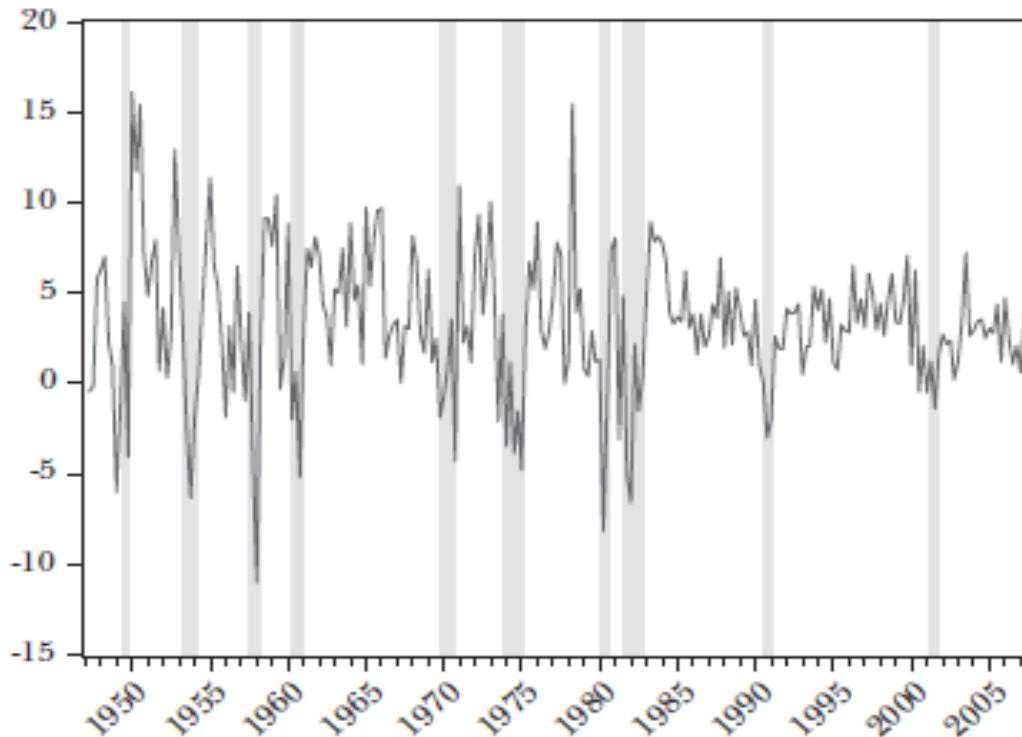
$$\sum_i^n \alpha_{it}^2 \sigma_{it}^2 + \sum_i^n \alpha_{it}^2 \left[\sum_{k=1}^K \beta_{ik}^2 \sigma_{kt}^2 \right] + 2 \sum_{j>i}^n \alpha_{it} \alpha_{jt} \left[\sum_{k=1}^K \beta_{ik} \beta_{jk} \sigma_{kt}^2 \right]$$

Positive co-movements over time in the cross section imply that the last cross-product above is positive.

A Bit of Background on The Great Moderation

GDP Growth, 1947–2007
(quarterly, annual rate in percent)

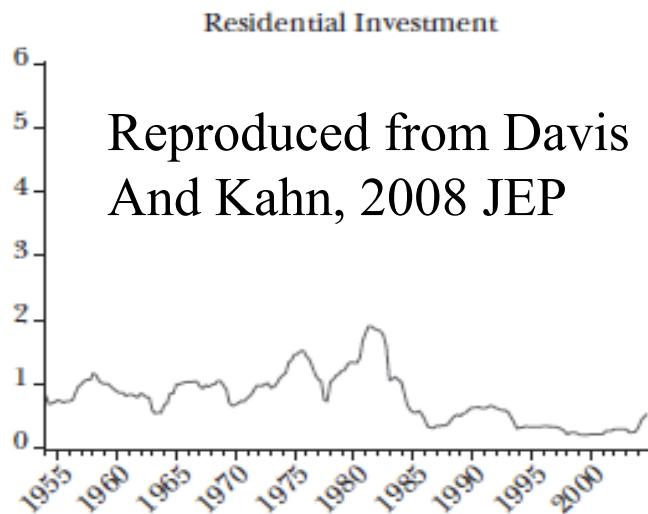
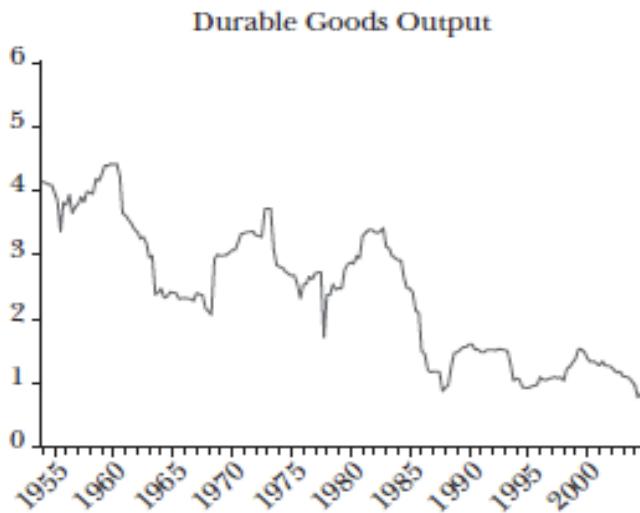
Reproduced from Davis
And Kahn, 2008 JEP



Source: National Income and Product Accounts.

Note: Shaded periods represent NBER-designated recessions

Volatility over Time in Key Categories
(five-year rolling standard deviations of quarterly annualized growth contributions in percent)



Reproduced from Davis
And Kahn, 2008 JEP



Overview of Davis et al. 2006 Paper

An empirical study of trends in the volatility and dispersion of business growth rates.

Key themes

- Publicly traded versus privately held
 - Resolution of puzzle turns on this distinction.
- Major shift in the economic selection process governing the risk/volatility profile of firms that go public
- Role of changes in business age, size, cohort and industry distributions

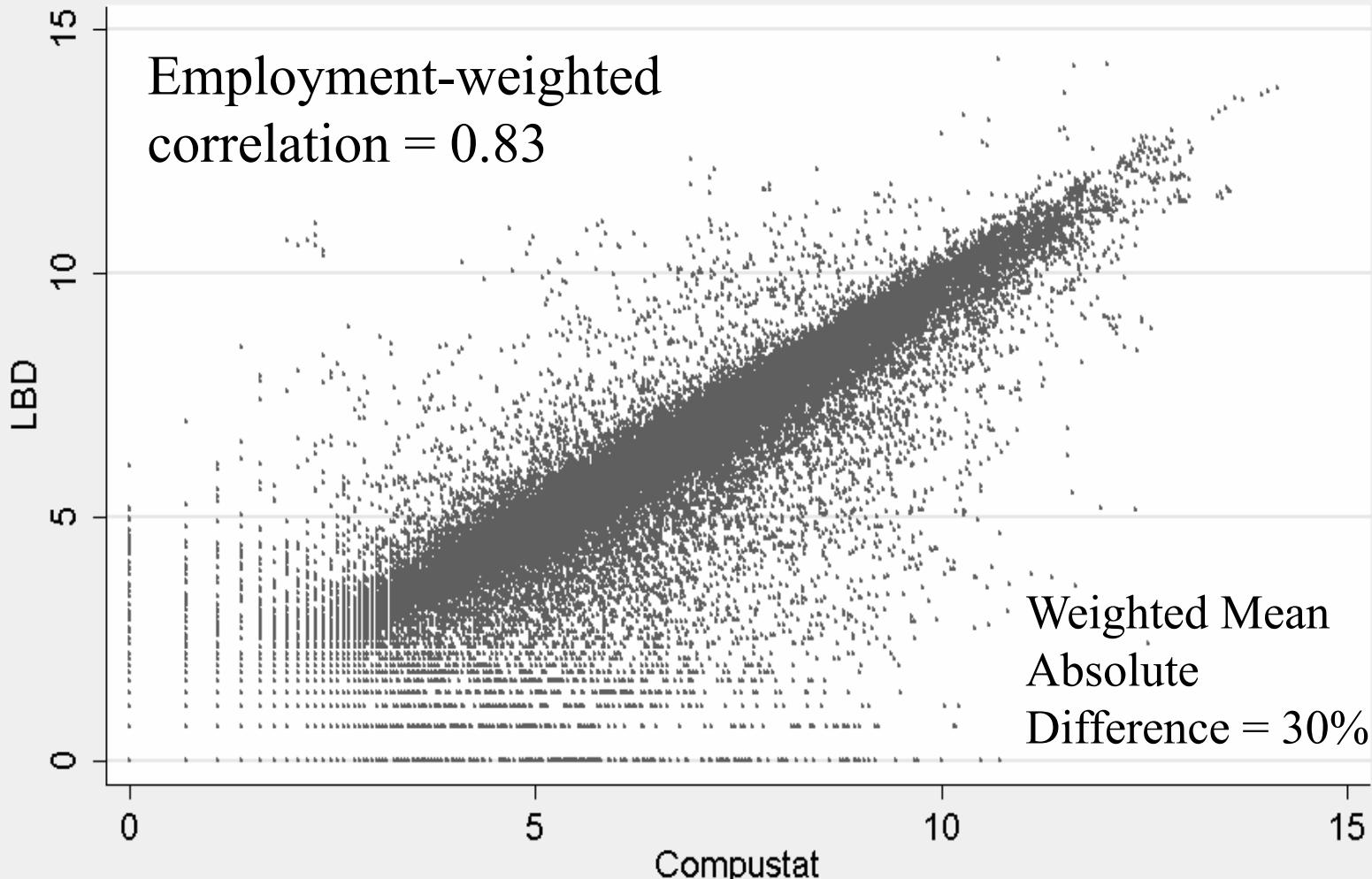
Longitudinal Business Database (LBD)

- Annual observations, 1976 to 2001 (now through 2014 or 2015)
- All establishments and firms with employees
- Employment, payroll, and other variables
- Employment concept: count of workers subject to U.S. payroll taxes in pay period covering 12th of March
- See Jarmin and Miranda (2002) on LBD.
- We limit analysis to nonfarm sector

COMPUSTAT

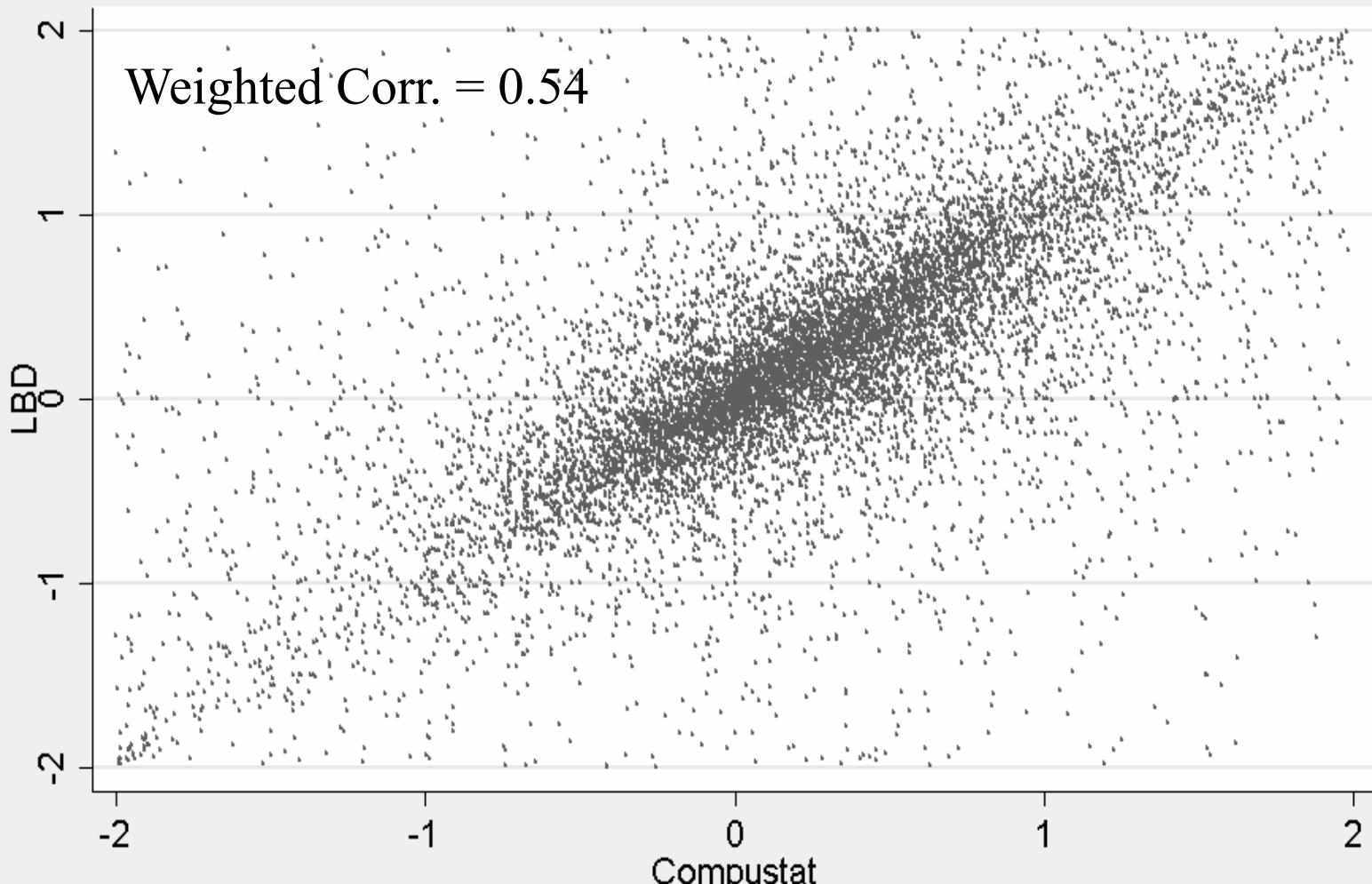
- Publicly traded, listed firms
- Annual data from 1950 to 2004 (since updated)
- Employment Concept: Number of company workers reported to shareholders
 - Annual average or end-of-year figure
 - Includes employees of consolidated subsidiaries, domestic or foreign
 - Missing data, measurement error
- We use COMPUSTAT for some exercises *and* to supplement the LBD with information on whether firms are publicly traded

Compustat to Business Register Log Employment



Source: Own Calculations from Compustat/LBD

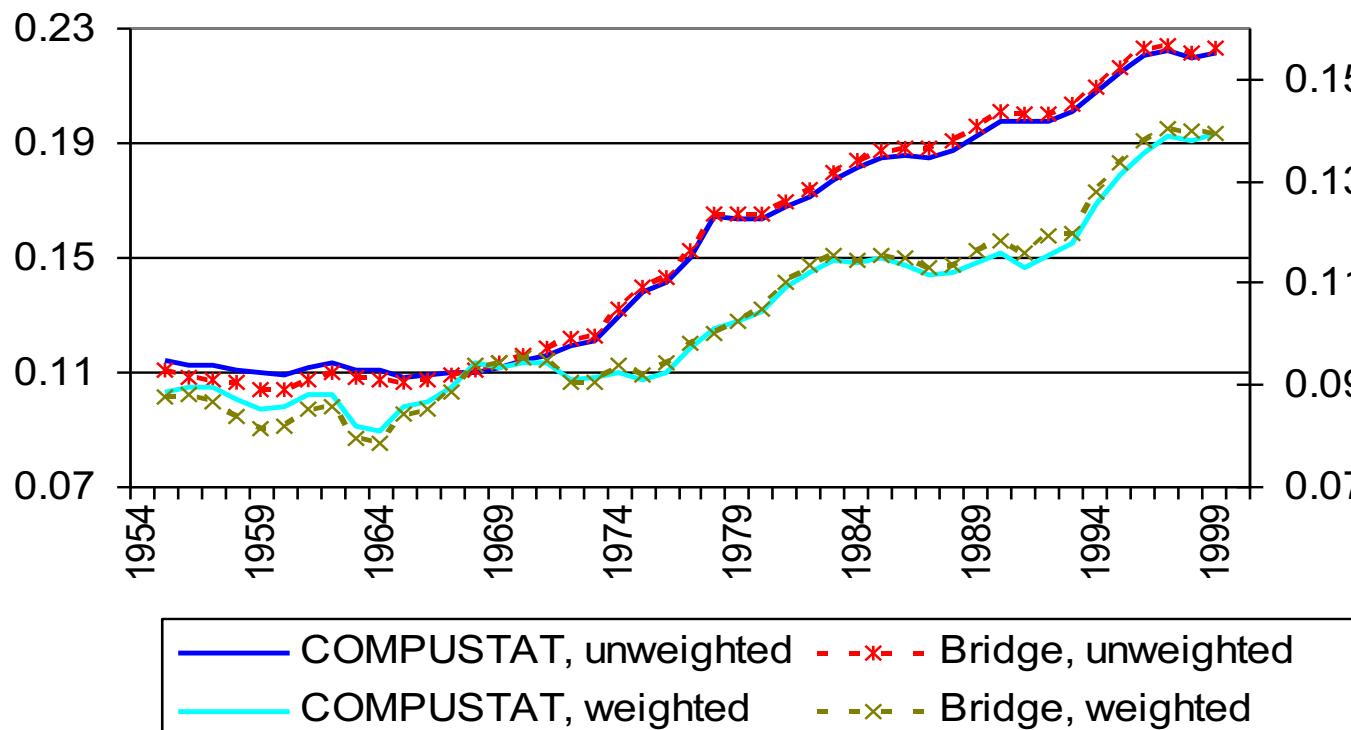
Compustat to Business Register 5-year Growth in Employment



Source: Own Calculations from Compustat/LBD

**Figure 3: Full COMPUSTAT
Compared to Bridge Cases**

**Average Volatility of Firm Employment Growth Rates:
COMPUSTAT and COMPUSTAT-LBD Bridge Compared**



**Figure 3: Full COMPUSTAT
Compared to Bridge Cases**

**Average Volatility of Firm Employment Growth Rates:
COMPUSTAT and COMPUSTAT-LBD Bridge Compared**

→ Restricting attention to publicly traded firms we can identify in the LBD has no material effect on measured firm-level volatility.

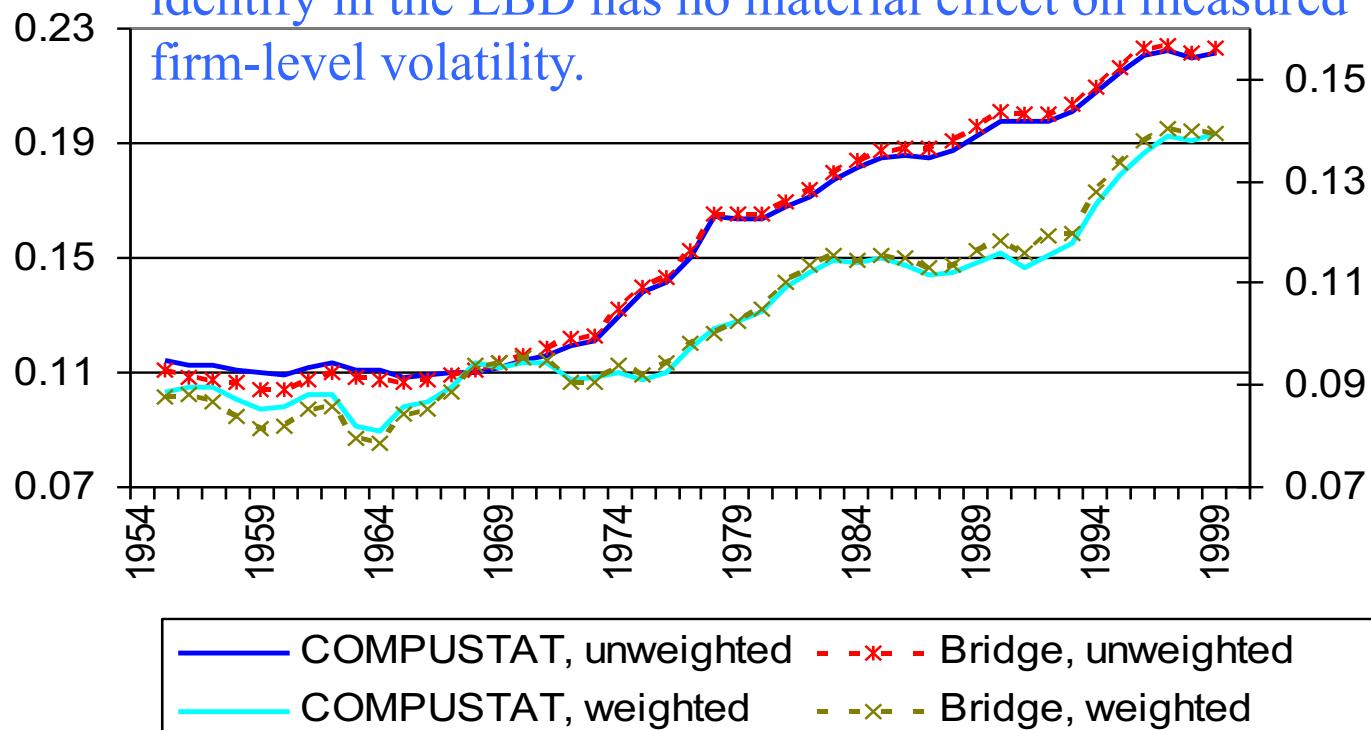


Figure 4(a): Volatility and Dispersion Compared, COMPUSTAT Data

Dispersion measured as Cross-Sectional Standard Deviation of Annual Employment Growth Rates

Publicly Traded Firms, Unweighted

Using LBD employment data and COMPUSTAT to identify publicly traded firms

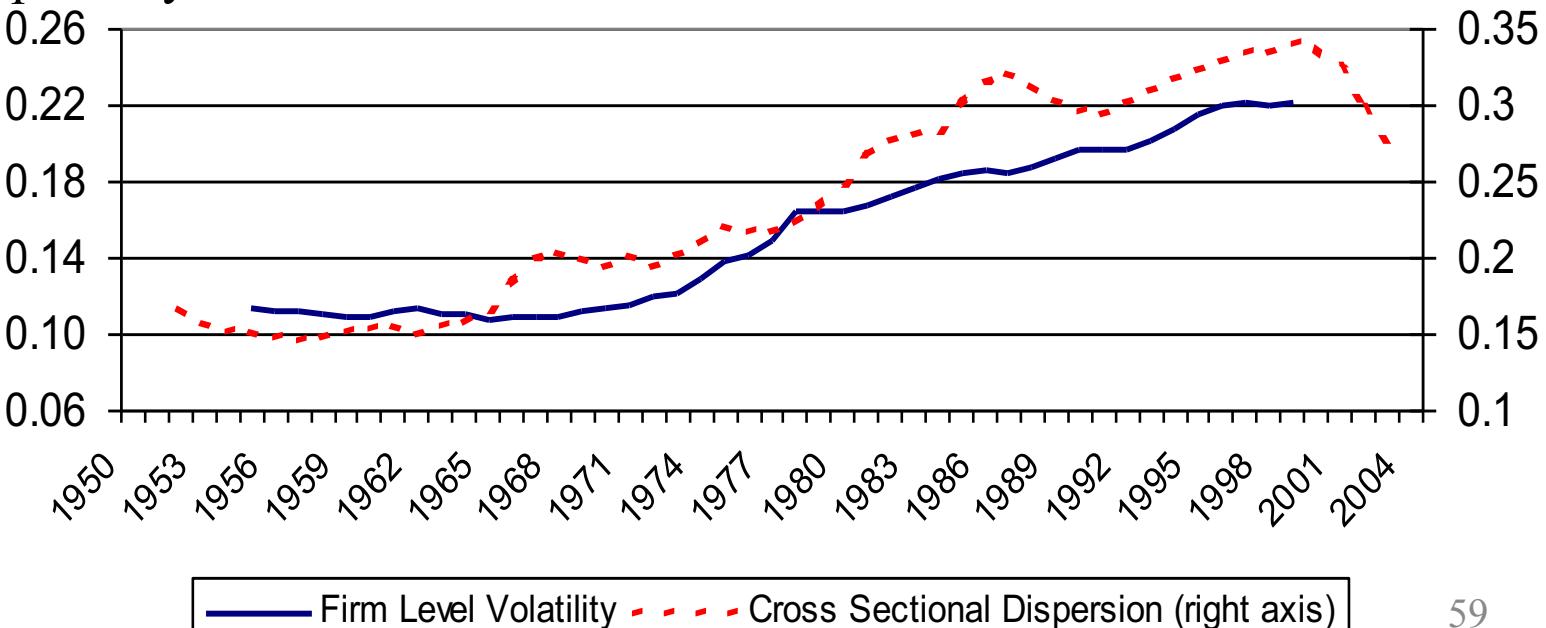
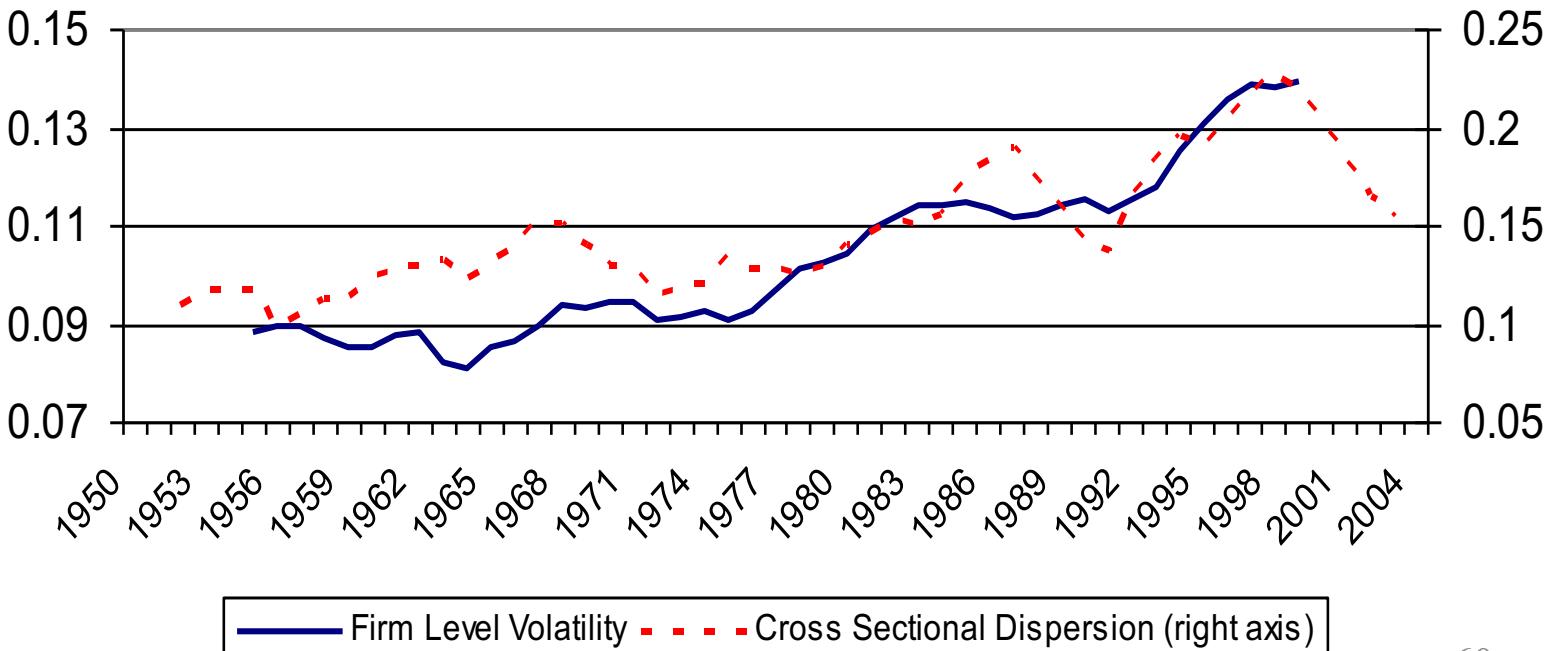


Figure 4(b): Volatility and Dispersion Compared, COMPUSTAT Data

Publicly Traded Firms, Employment Weighted

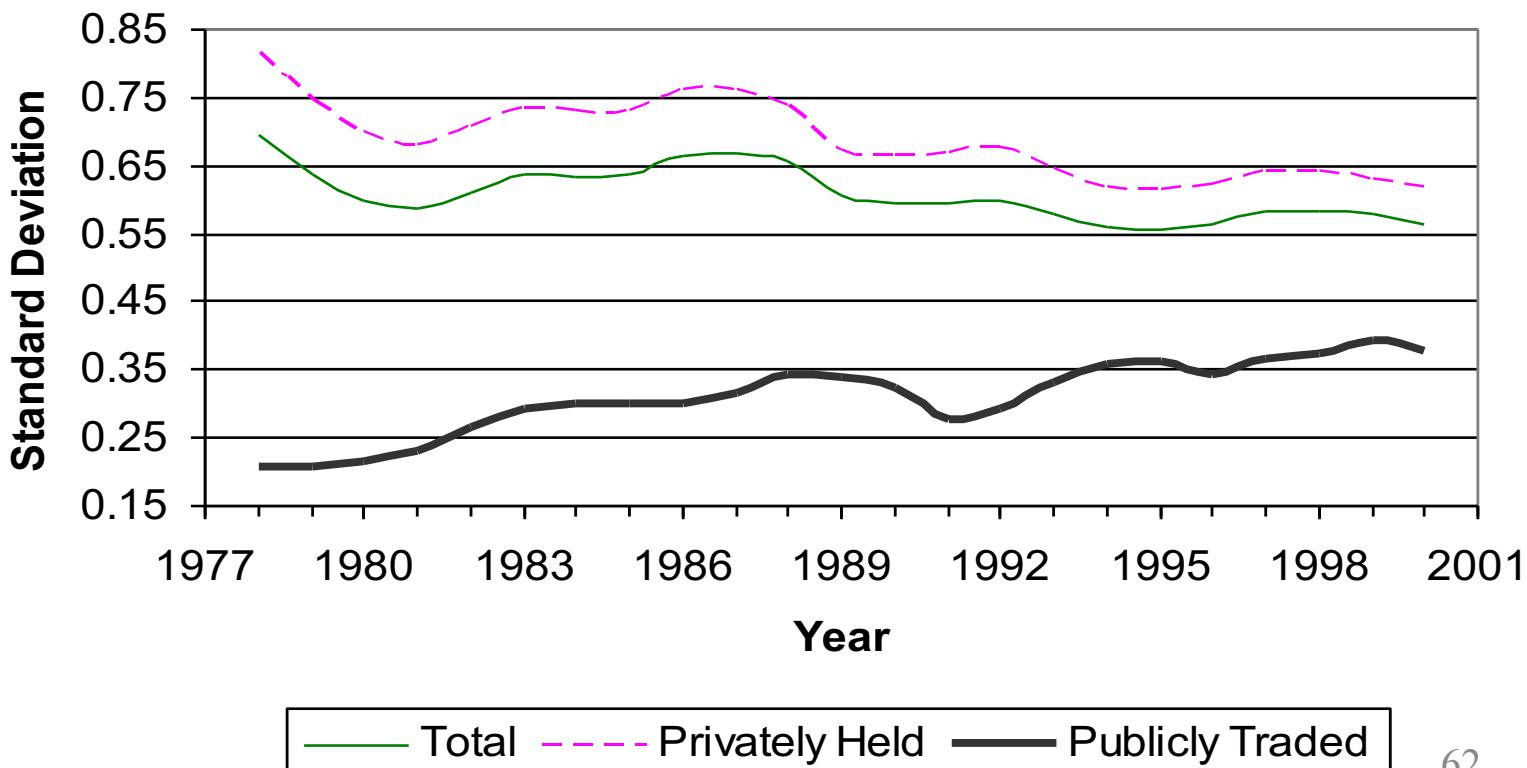


Preview of Our Main Findings

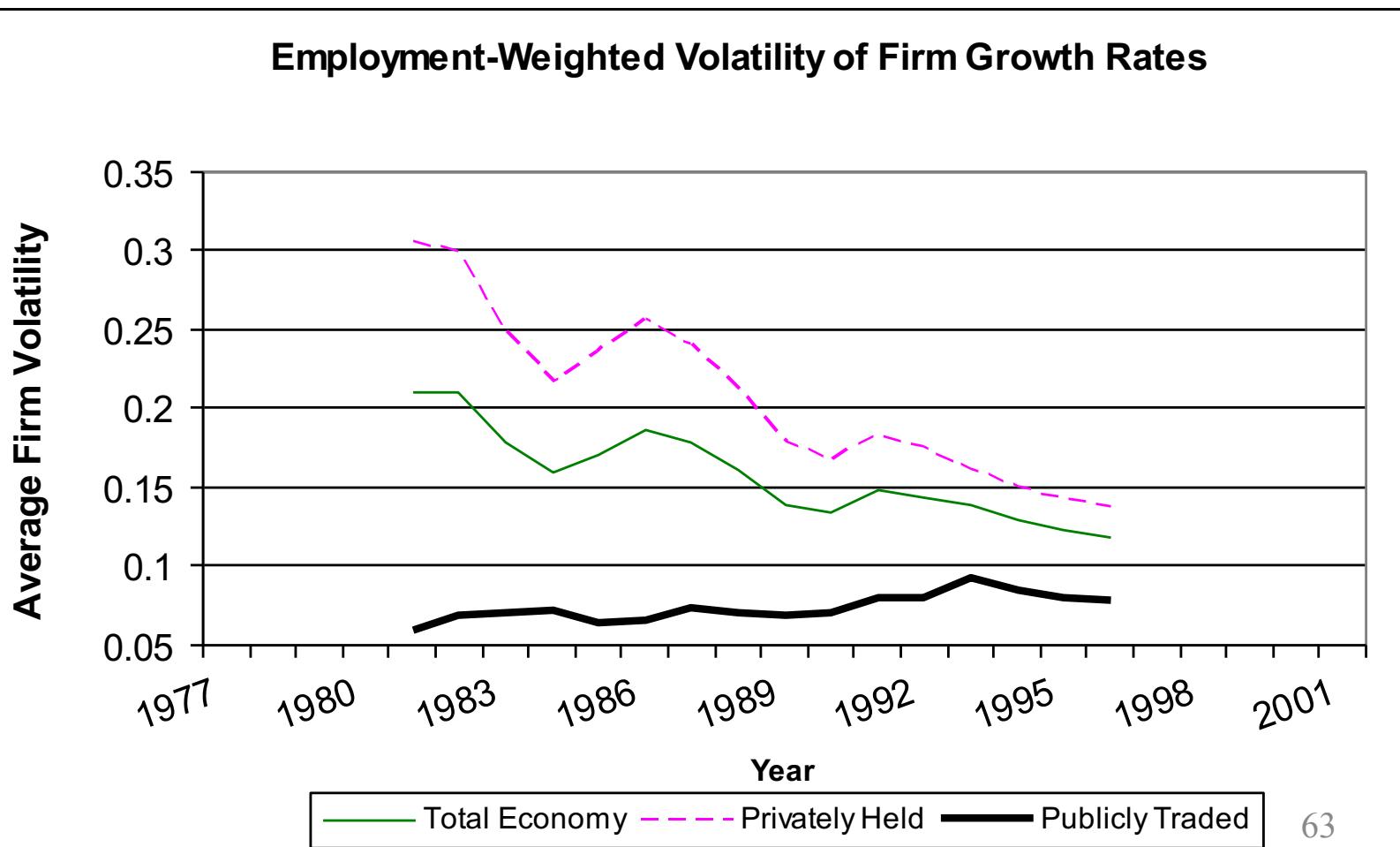
- Large secular decline in the cross-sectional dispersion of employment growth rates and in the magnitude of firm-level volatility
 - 40% drop in firm-level volatility since 1982
 - Pattern holds for all major industry groups
- Huge trend differences between publicly traded and privately held firms
 - LBD confirms rising volatility and dispersion for publicly traded firms
 - But overwhelmed by declines for privately held
 - “Volatility convergence” in all industry groups

**Figure 5: Dispersion of Employment Growth Rates
by Ownership Status, LBD Data**

**Employment-Weighted Dispersion of Firm Growth Rates,
Three-Year Moving Averages**



**Figure 5: Average Volatility of Employment Growth Rate
by Ownership Status, LBD Data**



Modified Volatility Measure, Allow the Window Length to Vary

$$\tilde{\sigma}_{it} = \left[\sum_{\tau=-4}^5 \left(\frac{\tilde{z}_{i,t+\tau}}{P_{it} - 1} \right) (\gamma_{i,t+\tau} - \bar{\gamma}_{it}^w)^2 \right]^{1/2}$$

of years from t-4 to t+5
for which $z_{it} > 0$.

$$z_{it} = .5(x_{it} + x_{it-1})$$

$$K_{it}$$

$$= P_{it} / \sum_{\tau=-4}^5 z_{i,t+\tau},$$

Fix the scaling
quantity over
the window
of the firm-
level volatility
measure.

$$\tilde{z}_{it} = K_{it} z_{it}$$

$$\sum_{\tau=-4}^5 \tilde{z}_{i,t+\tau} = P_{it}$$

By construction, the
sum of the rescaled
weights add up to P .

Correcting a typo
in the paper

Figure 6: Modified Volatility by Ownership Status

Modified Volatility, Employment Weighted

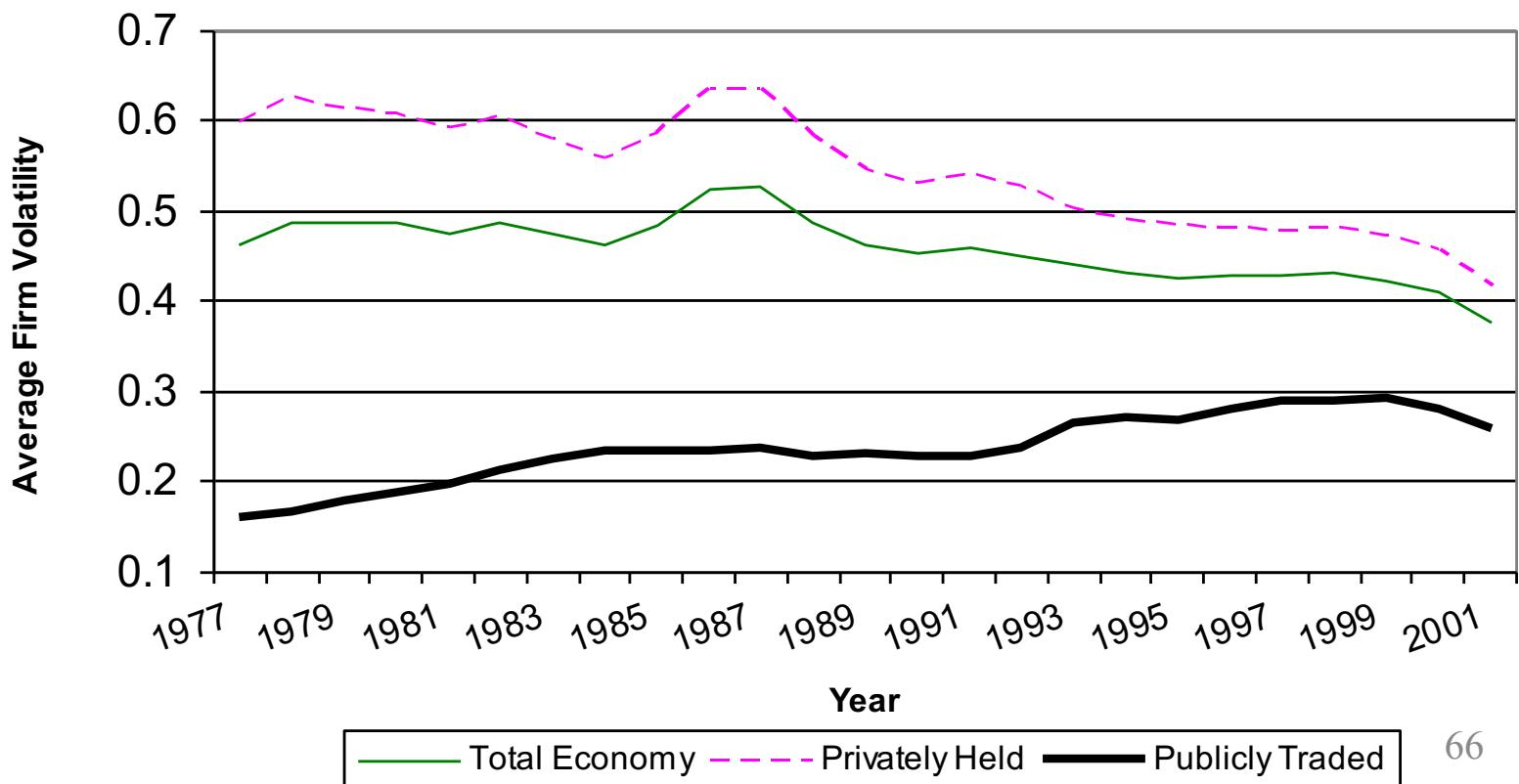


Table 2: Industry Level Outcomes, Modified Volatility Measure

	All Firms			Publicly Traded Firms			Privately Held Firms			Volatility Ratio: Privately Held to Publicly Traded		
Industry	1978	2001	Percent Change	1978	2001	Percent Change	1978	2001	Percent Change	1978	2001	Change
Minerals	0.54	0.41	-24.2	0.25	0.28	10.9	0.74	0.52	-29.8	3.0	1.9	-1.1
Construction	0.78	0.51	-34.5	0.33	0.34	1.3	0.82	0.52	-36.6	2.5	1.5	-0.9
Manufacturing	0.34	0.30	-12.9	0.16	0.21	28.7	0.53	0.35	-33.5	3.2	1.7	-1.5
TPU	0.37	0.34	-6.7	0.11	0.25	129.4	0.67	0.45	-32.8	6.3	1.8	-4.4
Wholesale	0.53	0.33	-36.5	0.16	0.24	45.6	0.58	0.36	-38.3	3.6	1.5	-2.1
Retail	0.56	0.36	-36.1	0.17	0.20	16.8	0.70	0.44	-37.5	4.2	2.2	-1.9
FIRE	0.44	0.39	-13.1	0.17	0.33	96.4	0.54	0.42	-22.6	3.3	1.3	-2.0
Services	0.59	0.41	-30.7	0.27	0.38	38.5	0.61	0.41	-32.4	2.3	1.1	-1.2
All	0.49	0.38	-22.9	0.17	0.26	55.5	0.63	0.42	-33.4	3.7	1.6	-2.1

(Basic) Firm-Level Volatility, 1982-1996, Percent Change by Industry

<i>Industry</i>	1982	1996	% Change
Minerals	0.24	0.15	-39
Const.	0.45	0.22	-52
Manuf.	0.13	0.08	-38
TPU	0.18	0.10	-44
Wholesale	0.24	0.11	-53
Retail	0.19	0.10	-46
FIRE	0.18	0.14	-23
Services	0.29	0.14	-53

(Basic) Volatility Convergence

<i>Industry</i>	Volatility Ratio: Privately Held to Publicly Traded		
	1982	1996	Change
Minerals	4.5	1.4	-3.1
Const.	6.4	2.8	-3.6
Manuf.	3.7	1.7	-2.0
TPU	3.9	2.0	-1.9
Wholesale	2.9	1.5	-1.4
Retail	3.3	2.1	-1.3
FIRE	3.2	1.2	-2.1
Services	1.7	1.0	-0.7

Figure 7: Dispersion of Establishment Growth Rates

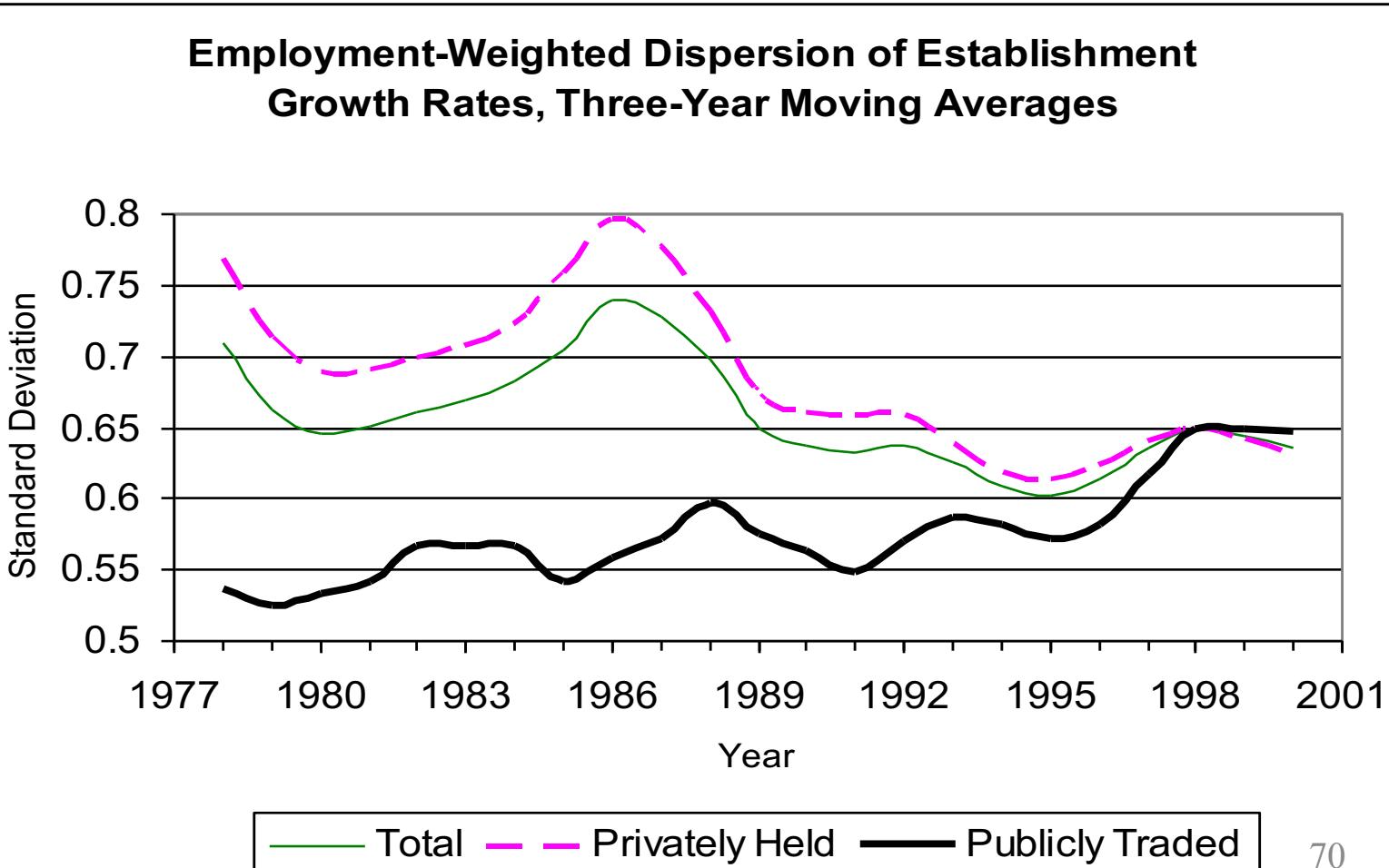


Figure 7: Modified Volatility of Establishment Growth Rates

Modified Establishment Volatility,
Employment Weighted

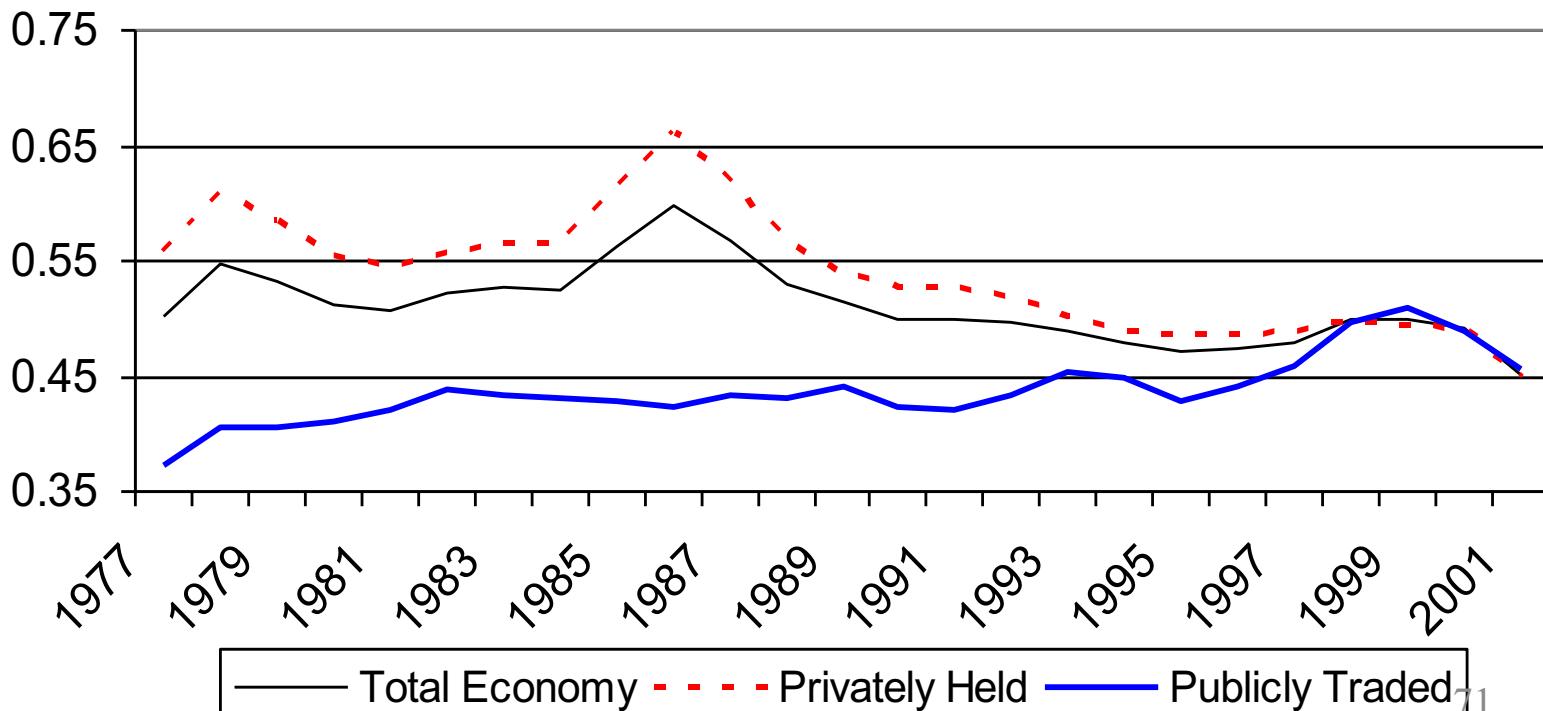


Table 3: Size, Age and Industry Effects

Fixing Employment Shares at 1982 Values for:	Average Volatility, All Firms			Average Volatility, Publicly Traded Firms			Average Volatility, Privately Held Firms		
	1982	2001	Percent Change	1982	2001	Percent Change	1982	2001	Percent Change
Size, Age and Industry	0.49	0.40	-17.7	0.21	0.24	10.5	0.60	0.47	-22.7
Industry	0.49	0.36	-25.6	0.21	0.24	11.2	0.60	0.41	-31.5
Age	0.49	0.41	-16.3	0.21	0.26	20.9	0.60	0.47	-22.7
Size	0.49	0.39	-20.7	0.21	0.26	21.5	0.60	0.43	-28.1
Actual Volatility	0.49	0.38	-23.0	0.21	0.26	21.4	0.60	0.42	-31.1

Volatility and dispersion differ by industry and especially by business size and age. To investigate whether shifts in activity across categories accounts for the volatility trends, we use a cell-based shift-share methodology where we compute the modified volatility for 448 age, size and industry cells: Age: entrants, 1, 2, 3, 4, 5, 6+ years of age (oldest Establishment), eight size categories, and eight industry groups

-- Fixing the industry distribution of employment at 1982 cuts the 21% rise in modified volatility among publicly traded by half. Fixing the age distribution of employment at 1982 accounts for 27 percent of volatility fall among privately held. This figure probably understates role of age distribution shift – see Table 4.

Figure 10: Industry Employment Shares, Publicly Traded Firms

Employment Shares Among Publicly Traded Firms,
Selected Industries

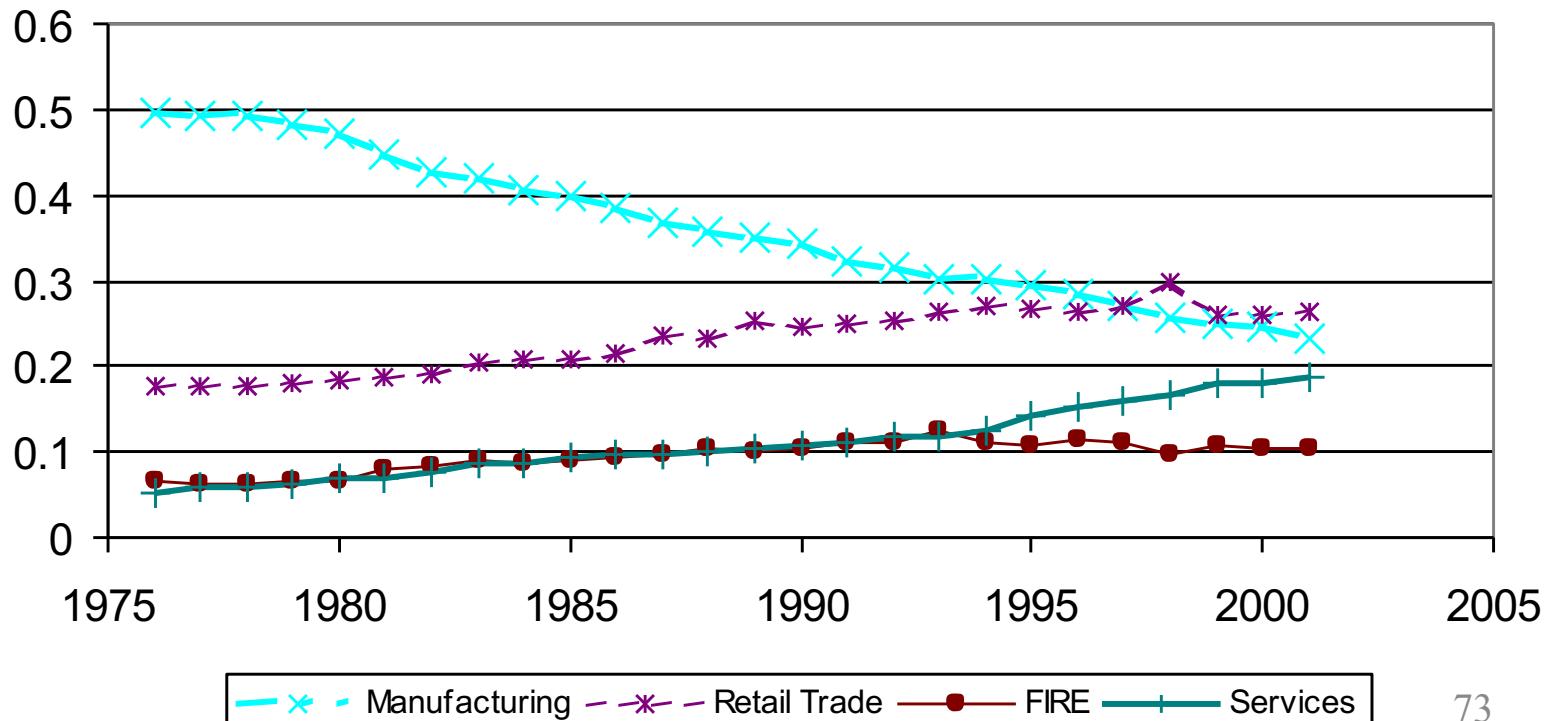


Table 4: Employment Shares and Volatility by Firm Age, Privately Held

	Percent of Employment		Firm Volatility		Percent Change In Volatility
Age in Years	1982	2001	1982	1996	1982-1996
Entrants	1.6	1.2	1.47	1.63	11.0
1	3.4	2.6	1.36	1.37	1.3
2	4.3	3.4	1.21	1.14	-5.2
3	4.8	3.3	1.00	0.90	-9.5
4	4.3	3.0	0.84	0.79	-5.9
5	6.0	3.0	0.66	0.65	-1.2
6+	75.6	83.6	0.47	0.38	-20.8
Overall			0.60	0.48	-20.2
Statistics for 2001	6-9 years	10-14 years	15-19 years	20-24 years	25+ years
Percent of Employment	10.2	11.1	11.6	10.2	40.5
Firm Volatility	0.45	0.37	0.32	0.30	0.28

Understanding Trends for Publicly Traded Firms

- Huge upsurge of newly listed firms (Fama-French, 2004)
 - # new lists (mostly IPOs) jumps from 156 per year in 1973-1979 to 549 per year from 1980-2001
 - 10% of listed firms are new each year from 1980 to 2001
- New lists became increasingly risky (FF, and Fink et al.)
 - New lists became increasingly risky relative to seasoned firms as measured by profitability and returns
 - Firm age at IPO fell from 40 years in the early 1960s to less than 5 years by the late 1990s. (Jovanovic-Rousseau 2001 data)
- Upsurge of new lists explains most or all of rise in volatility of idiosyncratic component of equity returns (FF, Fink et al.)
- Points to a decline in the cost of equity for risky firms and firms with distant payoffs

Figure 11. Modified Firm Volatility By Cohort, 1951-2004

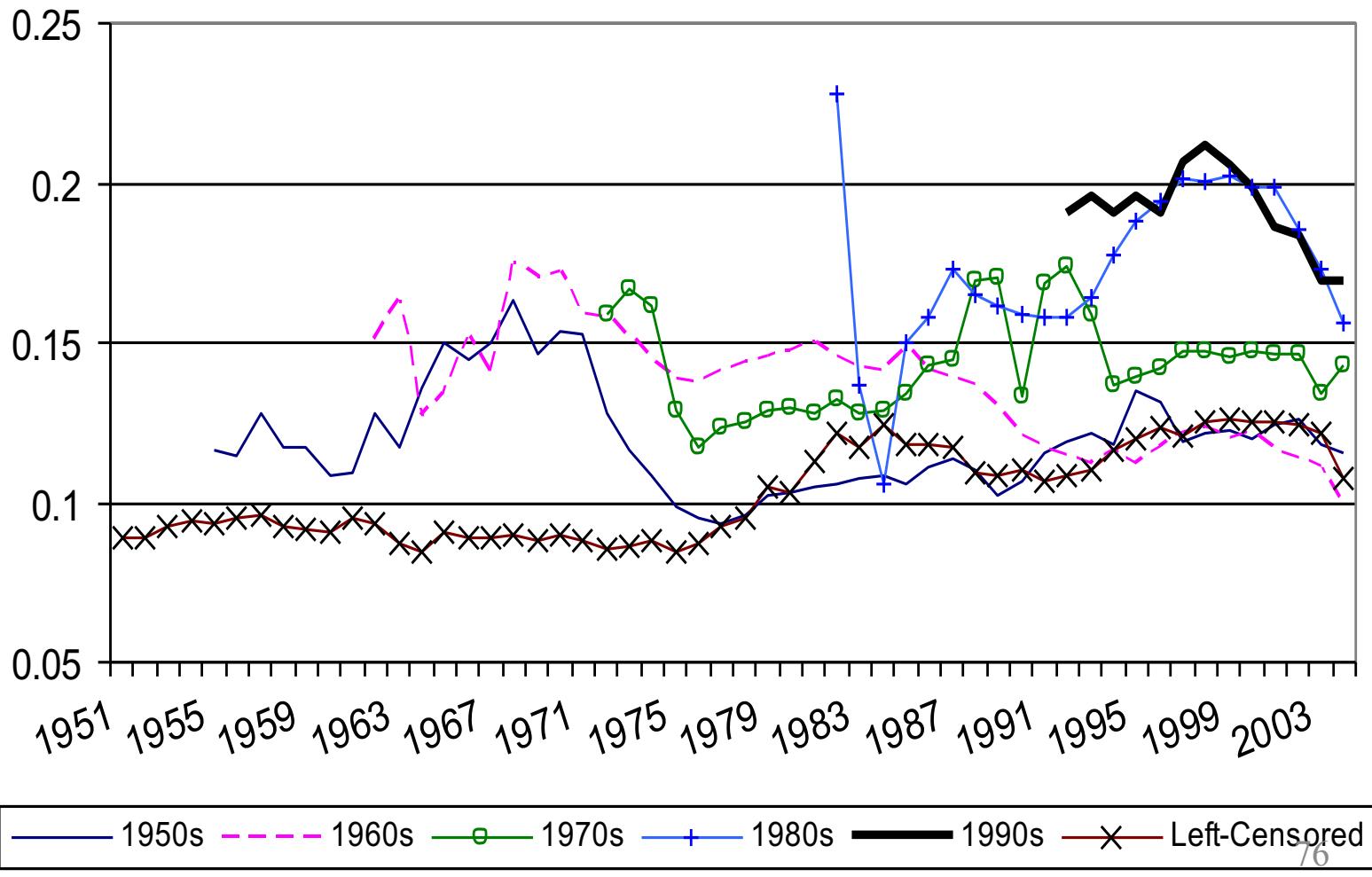
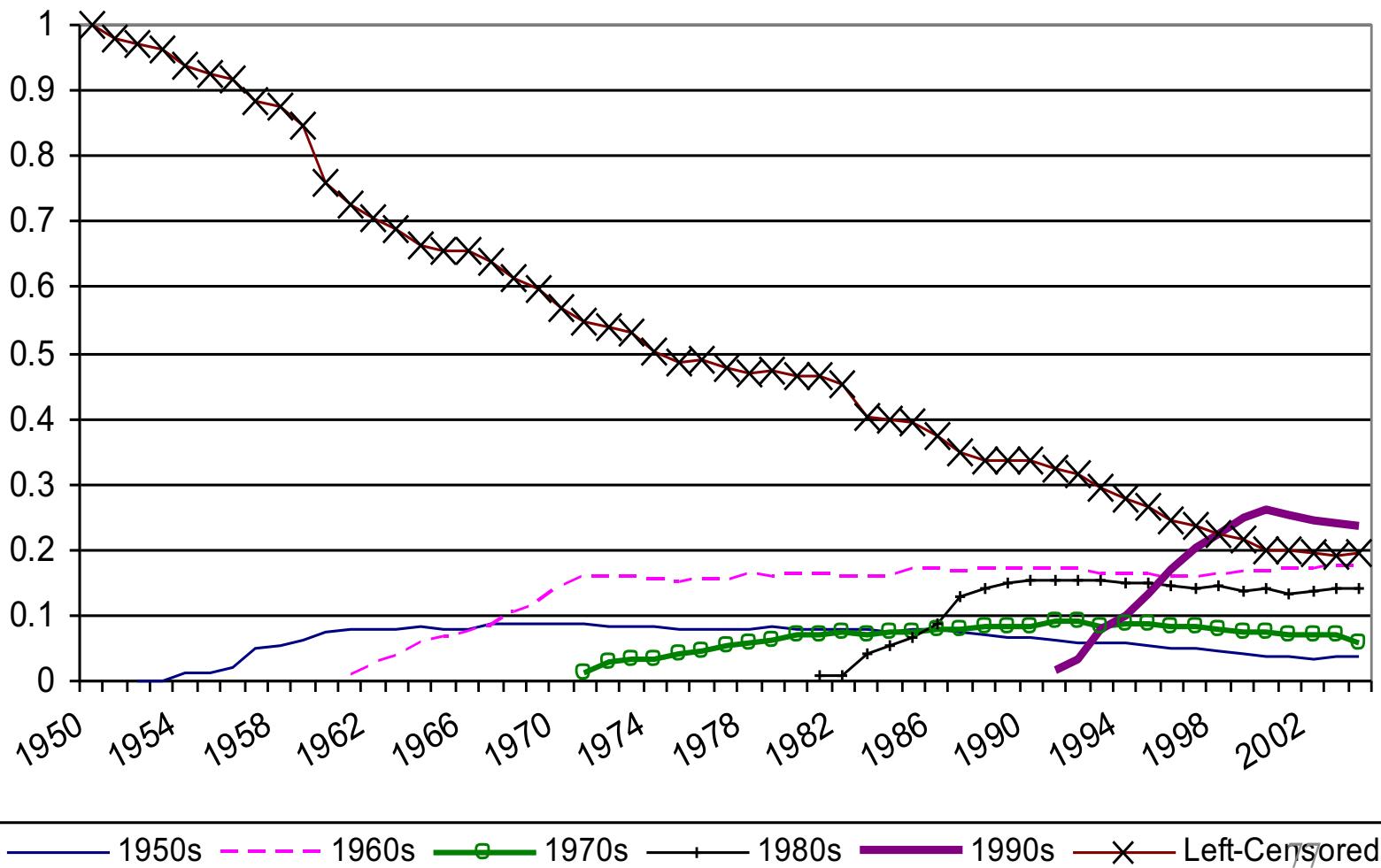
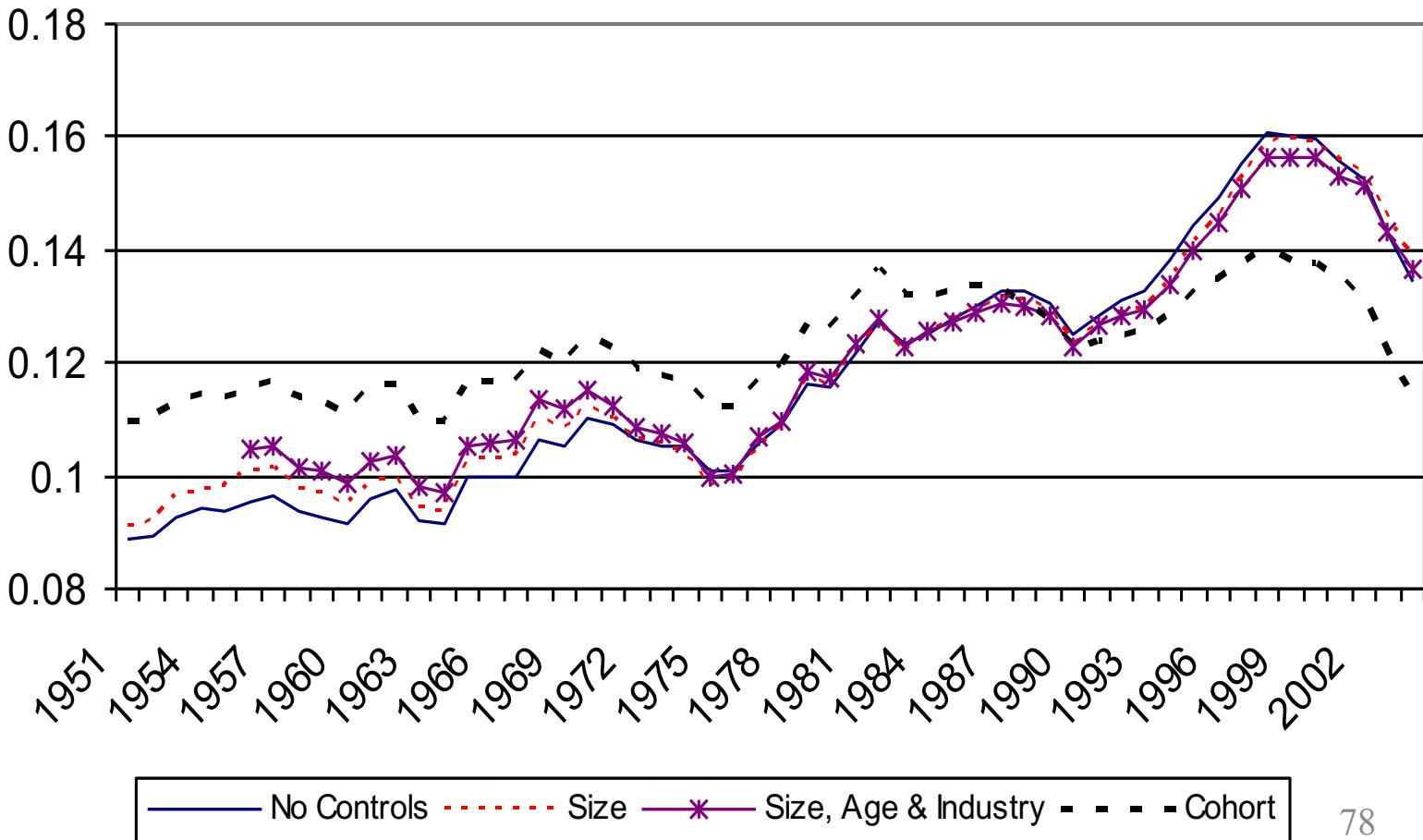


Figure 12. Share of Employment By Cohort,
1950-2004



Modified Volatility among Publicly Traded Firms: The Role of Size, Age, Industry and Cohort Effects



**Table 5: Cohort Effects in the Volatility Trend among Publicly Traded Firms,
COMPUSTAT Data**

Time Interval	Initial Volatility ×100	Change in Volatility ×100	Percentage of Volatility Change Accounted for by Cohort Effects
1951-1978	8.87	2.03	49.1
1951-1999	8.87	7.14	59.4
1951-2004	8.87	4.55	90.0
1978-1999	10.89	5.11	63.5
1978-2001	10.89	4.67	67.4
1978-2004	10.89	2.52	122.9

Summary of Main Findings

1. Average firm-level volatility down sharply
 - 23% decline from 1978 to 2001 using our preferred volatility measure (Figure 6), 29% since 1987
 - Pattern holds for all industry groups
2. Huge trend differences between publicly traded and privately held firms
 - Volatility convergence in all industry groups
3. Shift to older firms accounts for much of volatility decline among privately held firms
4. Large upsurge and increasingly risky nature of newly public firms accounts for most of volatility rise
 - The process governing selection into the set of publicly traded firms shifted markedly after 1979
 - Casual empiricism suggests it shifted again after early 2000s, perhaps due to Sarbanes-Oxley.

Figure 15: Selection on Risk and Firm Ownership Status

Publicly
Traded
Firms

Simple selection story doesn't fit the facts. It implies, contrary to the evidence, a volatility rise in both groups of firms and a rising share of employment at publicly traded firms. Neither occurred.

Our results also present a challenge to Schumpeterian theories of growth – the large decline in firm-level and establishment-level volatility that we document coincided with a period of impressive productivity gains.

- This coincidence belies any close and simple positive relationship between productivity growth and the intensity of creative destruction, at least as measured by firm-based or establishment-based measures of volatility in employment growth rates.
- Perhaps there has been a big increase in pace of restructuring, experimentation and adjustment within firms.
- Perhaps more intense creative destruction among publicly traded firms, partly facilitated by easier access to public equity by high-risk firms, has been sufficient to generate the commercial innovations that fueled productivity gains throughout the economy.

Related Additional Readings

1. For more on the changing nature of selection into the set of publicly traded firms, read Fama-French (2004) and Brown and Kapadia (J. of Financial Economics, 2007)
2. For an interesting theoretical and empirical effort to explain the diverging trends of publicly traded and privately held firms, see “Contrasting Trends in Firm Volatility” by Mathias Thoenig and David Thesmar, AEJ Macro, October 2011.
3. On Schumpeterian theories of growth through creative destruction, see Aghion and Howitt (1998) and Caballero (2006). Chapter 2 of Caballero’s book has a very nice review of the empirical work on the role of factor reallocation in productivity growth. See, also Bartlesman and Doms (2000) and Foster et al. (2001).

Related Additional Readings

4. For more on the Great Moderation, see Davis and Kahn (2008) and references therein.
5. For a study that draws on similar data sources to provide an updated characterization of trends in U.S. business volatility, see "The Secular Decline of business Dynamism in the United States" by Decker, Haltiwanger, Jarmin and Miranda. They show that business volatility has trended downward since the early 2000s for privately held *and* publicly listed firms.
6. We will consider the labor market consequences of declining business volatility later in the course in our discussion of "Labor Market Fluidity and Economic Performance."