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 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, establishments also linked to their employees who are followed longitudinally

• Advances in data storage and computing power greatly increase the scope for building these databases and using them as research tools.
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 all businesses with 1+ employees
Other Business Databases

• Other longitudinal business databases derive from panel surveys conducted by statistical agencies and from proprietary sources created for commercial purposes.

• Some of the most exciting research ideas on the margin combine large “backbone” databases like the LBD and BED with smaller, targeted sources that contain rich information about particular aspects of business behavior and outcomes.
3. 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
   - Heavily exploited in economics research

4. Various Censuses of Business (e.g., Retail Trade)
   - Extensive coverage of plants and firms about once every five years, large set of measures

5. ILBD: LBD + revenue, industry and ownership data on businesses with no employees. See Davis et al. (2009).
Selected Other U.S. Business Databases

6. Job Openings and Labor Turnover Survey (JOLTS): BLS establishment-level survey of job vacancies and worker flows (quits, layoffs, hires, etc.)

7. 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

8. Dealogic: Another commercial platform with data on financial characteristics of businesses, business sales, etc. www.dealogic.com/
Some Applications

1. Job creation & destruction statistics
   - Briefly discussed below
   - Treated at greater length in old lecture notes for Section II of the reading list (not covered in class)

2. Identifying and correcting sample design flaws to produce better aggregate statistics
   - Briefly discussed below

3. Exploiting cross-sectional relationships to produce synthetic time series data
   - Briefly discussed below
Some Applications

4. Assessing the effects of private equity buyouts on employment, job flows, employee compensation, and productivity
   – This lecture

5. Reassessing trends in business volatility
   – This lecture

6. Measuring labor market fluidity and assessing its effects on economic performance
   – The lecture for part III of the reading list
Some Applications

7. Identifying and quantifying spatial agglomeration spillovers on productivity
   – Greenstone et al. in the JPE (2010)

8. Estimating the employment effects of credit market disruptions
   – Chodorow-Reich, QJE (2014)
   – A very successful job market paper!

9. Investigating how the availability of bank financing affects productivity of small firms
   – Krishnan, Nandy and Puri, NBER w.p. 20149 (2014)
Some Applications

This lecture treats applications 1, 2 and 3 briefly, then digs into applications 4 and 5 in detail. Later in the course, we will look closely at other applications:

- Employer behavior on the hiring margin, with implications for the matching function and search-theoretic models
- Earnings losses associated with job displacement and their sensitivity to aggregate conditions at the time of displacement
Application 1: Constructing Job Creation & Destruction Statistics

- See *Job Creation and Destruction* by Davis, Haltiwanger & Schuh (1996).
- U.S. statistical agencies now use the LBD, BED and other sources to produce annual and quarterly job flow measures on an ongoing basis.
- Job flow statistics are now available for many other countries as well.
- Similar measurement methods have been used to produce statistics on gross worker flows, gross capital flows, and gross credit flows.
**Labor Market Flows: Some Definitions**

- **Job Flows**
  - *Job Creation*: employment gains at expanding and new employers (e.g., expanding and new establishments) between two points in time
  - *Job Destruction*: employment losses at employers that contract or exit

- **Worker Flows (Employer Side)**
  - *Hires*: Flow of new workers hired in a given period
  - *Separations*: Flow of workers who separate from their employers in a given period
    - Quits
    - Layoffs and Discharges for Cause
    - Transfers, Retirements and Deaths

- **Worker Flows (Individual or Household Side)**
  - *Job-to-Job Flows*: Transitions from one employer to another without a measured non-employment spell
Net Employment Change

≡ Creation - Destruction
   \[\text{Job Flows}\]

≡ Hires - Separations
   \[\text{Worker Flows}\]
An Expanding Firm

Unemployment

Previous Employer

Hires (Inflow)

Out of the Labor Force

Hires - Separations = Jobs Created

New Employer

Separations (Outflow)

Out of the Labor Force
Some 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. Some evidence displayed below ...
- Worker and job flows are tightly linked in the cross section and over time. See next slide and Davis et al. paper in the 2010 American Economic Review: Macro
- Job flows and worker flows trended strongly downward in recent decades. See two slides on ...
Figure 5: The Cross-Sectional Relationship between Worker Flows and Job Flows

Note to Figure 5: This figure, a simplified version of Figure 6 in Davis, Faberman and Haltiwanger (2012), is constructed from establishment-level JOLTS data pooled from 2001Q1 to 2010Q2.
Quarterly Rates of Worker Reallocation, Job Reallocation & Churn, U.S. Nonfarm Private Sector

Worker Reallocation = Job Reallocation + Churn
  (Hires + Separations)             (Creation + Destruction)

Annual Rates of Job Reallocation Across Firms and Establishments, U.S. Nonfarm Private Sector

Reproduced from “Labor Market Fluidity and Economic Performance” by Davis and Haltiwanger (2014)
Gross Flows of Credit, Capital, and Products

Several studies apply job flow measurement methods to study and analyze gross credit flows across borrowers, gross flows of physical capital across producers, and gross product creation and destruction. Some Examples:

• Craig and Haubrich, 2013. “Gross Loan Flows,” *Journal of Money, Credit and Banking*.
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 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 understate worker flows and job openings, and they (probably) misstate the relative cyclicality 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 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 published statistics but equally variable according to our adjusted statistics.
• BLS has revised its published JOLTS statistics since 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.
Application 3: Exploiting C-S Relations to Construct Synthetic Time-Series Data

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

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

- BED data on $f$ + model-based $\hat{\nu}$ for 1990-2001
- BED data on $f$ + JOLTS-based $\nu$ for 2001-2010.
Application 3: Exploiting C-S Relations to
Constructing Synthetic Time-Series Data

- Statistical model + complete quarterly data on the cross-sectional distribution of establishment-level growth rates $\rightarrow$ 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!
Layoffs move with job destruction. Quits move opposite to both.

This chart and the next two are reproduced from “Labor Market Flows in the Cross Section and Over Time,” by Davis, Faberman and Haltiwanger, Journal of Monetary Economics, January 2012.
Hires tend to move with job creation but are more volatile.
Layoff Rates Compared to Other Job Loss Data

- Job Destruction (left axis)
- Layoffs (Left Axis)
- Unemployment Inflows, CPS (Left Axis)
- Initial UI Claims (Right Axis)

Percent of Employment
This figure highlights an important aspect of U.S. labor market dynamics: Recessionary spikes in unemployment inflows are dominated by job loss.
Application 4:
Estimating the effects of private equity buyouts on employment, job flows, employee compensation, and productivity
Private Equity, Jobs, and Productivity

Steven J. Davis, John Haltiwanger, Kyle Handley
Ron Jarmin, Josh Lerner, and Javier Miranda

Forthcoming, American Economic Review
Motivation

Why we chose to work on this topic:

• Private equity is an interesting and increasingly common way to organize ownership, control and resource allocation.

• The effects of private equity buyouts on target firms and their workers is an important economic question and a big political/social issue.

• We had much better data and a much better empirical strategy for assessing the employment effects of private equity buyouts.

• We were genuinely curious (diffuse priors).
Chief Questions

1. What happens to job creation and destruction at target firms and their establishments in the wake of private equity (PE) buyouts?

2. What happens to total factor productivity (TFP) at target firms and establishments?
   – How are productivity developments related to job reallocation?

3. What happens to compensation per worker at PE targets?
Private Equity Buyouts

• Controlling equity stakes in target firms by professionally managed partnerships (PE)
  – PE group exercises significant oversight until “exit.”
  – Most PE buyouts are highly leveraged.
  – Some involve a change in management.

• We focus on mature and later-stage target firms – i.e., excluding VC-backed firms.

• Short-hand: “Leveraged buyouts,” “LBOs,” or “buyouts.”
Worldwide Growth of PE

• Private equity as an asset class and organization form has spread throughout much of the world:
  – Buyout activity remains concentrated in North America and Europe but has grown rapidly in Asia.

• More than 21,000 PE buyouts worldwide from 1970 to 2007 (Kaplan-Stromberg [2009]):
  – $2.7 trillion from 2000 to 2007 alone.
  – Steep drop in PE activity in the wake of global financial crisis.
Private Equity and Jobs: A Politically Charged Issue

“[S]ome financial investors don’t waste any thoughts on the people whose jobs they destroy. They remain anonymous, have no face, fall like a plague of locusts over our companies, devour everything, then fly on to the next one.”

-- Franz Müntefering, April 2005, Former Vice Chancellor of Germany, Speaking about hedge funds and private equity
Private Equity and Jobs: A Politically Charged Issue

“`leveraged buy-outs’ leave the company saddled with debt and interest payments, its workers are laid off, and its assets are sold, ... benefiting neither workers nor the real economy.”

Typically it’s easier to decrease costs quickly by cutting heads, which is why buyouts have typically been accompanied by layoffs.”

-- John Adler, Service Employees International Union, May 2007
Two Views from Private Equity

1. Many private equity targets are in distress or in need of restructuring before acquisition.
   – They would have cut jobs in any event, but private equity helps turn them around and restore profitability and job growth.
Two Views from Private Equity

2. Yes, we slash jobs in some buyouts, but we also create new jobs by building new plants, opening new facilities and redirecting capital and labor to more productive uses.
• Mitt Romney’s presidential campaign greatly amplified public attention on private equity.
  – For my contribution to the political debate, see “Private Equity Is a Force for Good” in The Atlantic (with Kevin Hassett) at www.theatlantic.com/business/archive/2012/01/private-equity-is-a-force-for-good/251419/

• Research Moral: It’s nice to be lucky – we began working on private equity several years before Romney became the Republican presidential nominee – but the key lesson is to write good papers that address important questions. If you do that consistently, the world will find you.
Some High-Profile Responses to Concerns about PE and Employment

- *The Economic Impact of Private Equity in the UK*, British Venture Capital Association [2006].
- *Private Equity and Jobs*, Private Equity Council [2008].

These studies suggest that private equity has a positive impact on job creation.
Issues and Weaknesses In These Studies

- Mix of VC-backed firms and buyout targets
- Reliance on surveys of uncertain quality ➔ concerns about representativeness & accuracy
- Inability to discern where jobs are being created and destroyed (domestic v. abroad)
- Lack of suitable controls
- Inability to disentangle organic growth from acquisitions and divestitures
- Inability to investigate how private equity affects reallocation within firms
Other Studies of PE Buyouts

• Many previous empirical studies, some of high quality.
  – Small, selected samples and crude controls
  – See our paper for references and discussion
  – We also discuss, briefly, several case studies

• No previous empirical study simultaneously follows target firms and their establishments.
  – Ability to follow firms & establishments is essential for an understanding of how PE affects employment, job reallocation and TFP growth.
Empirical Method: Overview

1. Compare PE targets to controls defined in terms of industry, size, age, and multi-unit status
   - Thousands of PE buyouts from 1980 to 2005.
   - Matched to the universe of firms and establishments in the U.S. Longitudinal Business Database (LBD).
   - Follow targets and controls before and after buyout.
   - Use LBD to disentangle organic changes from post-buyout acquisitions and divestitures

2. New decomposition of firm-level productivity changes that combines simple identities with diff-in-diff estimates of treatment effects.
Our Data Sources

• Capital IQ data on private equity transactions: roughly 5,000 buyouts of U.S. firms from 1980-2005.

• Supplemented with data from Dealogic, Thompson Reuters SDC, COMPUSTAT, VentureExpert, and newspaper articles

• Integrated into the Longitudinal Business Database (LBD) at the U.S. Bureau of the Census:
  – *Universe* of private businesses from 1975 to 2005.
  – Annual data on business name, EINs, employment, payroll, industry, location.
  – *Longitudinal* data on firms and their establishments.

• Further integrated with Census of Manufactures (CM) and Annual Survey of Manufactures (ASM) so that we can construct TFP measures
Sample and Matching

- ~5,000 U.S. target firms acquired in private equity buyouts from 1980 to 2005
- We match about 3,200 firms operating 152,000 U.S. establishments.
- 71% match rate on a value-weighted basis
- Descriptive statistics: 1980-2005
- Establishment-level analysis: 1980-2000
- Productivity analysis: Mfg. only, 1980-2003
Figure 2: Employment at Matched Targets as of the Buyout Year, 1980 to 2005

- Percent of LBD Employment
- Target Employment in Thousands, Right Axis
Rough calculation: More than 7% of private sector jobs came under control of private equity (via buyouts) at some point from 1998 to 2007.
How Do Buyout Targets Compare To Private Sector as a Whole?

- Establishments operated by buyout targets are older and larger than average.
- Size and age differences partly reflect a disproportionately large share of PE buyout activity in Manufacturing.
- Targets grow more slowly in the year before buyout.
Figure B.1B: Industry Distribution of Employment, Buyout Targets Compared to the Full LBD, 1981 to 2001
Figure B.1A: Industry Distribution of Employment, Buyout Targets Compared to the Full LBD, 2002 to 2005
Figure B.2A: Distribution of Employment by Firm Size (Number of Employees), Buyout Targets Compared to Full LBD, 1980-2005
Figure B.2B: Distribution of Employment by Age of Firm’s Oldest Establishment, Buyout Targets Compared to Full LBD, 1980-2005

- Full LBD
- Buyout Targets Only

- a. 0-4
- b. 5-9
- c. 10+
Establishment-Level Analysis

• Track target establishments forward and backward in time relative to event year:
  – Net employment growth rate
  – Cumulative employment change
  – Gross job creation and destruction rates
• Do the same for controls, and compare outcomes for targets and controls
• **Question:** What happens to employment at target establishments before and after buyout event relative to controls?
Controls and Analysis Sample

• 72 industries, 10 firm size groups, 6 firm age groups, multi-establishment dummy, and 24 distinct transaction years. Taking the cross product
  – About 8,000 control cells per year, many unpopulated
  – 190,000 control cells when pooled over years

• About 4.9 million controls and 152,000 targets in our full establishment-level analysis sample
  – For a given target, controls are all units in same industry-size-age-MU-year cell not owned by a PE-backed firm.
Employment Trajectory of Target Establishments, All (Matched) Buyouts that Occurred from 1980 to 2000, Using Employment Data from 1975 to 2005

Years Before or After Buyout Event

Buyout Year

[Graph showing employment trajectory with peaks at buyout year and changes before and after the event]
Figure 3A: Comparison of Employment Trajectory for Target Establishments to Controls, Buyouts from 1980 to 2000
Figure 3B: Employment Growth Rate Differences before & after Buyout Year, Target Establishments Minus Controls, Buyouts from 1980 to 2000
Job Creation Rates before & after Buyout Year, Targets Minus Controls

Job Destruction Rates before & after Buyout Year, Targets Minus Controls
What’s the Economic Quantity of Interest?

• Suppose each establishment has outcomes with and without “treatment” given by $y_1$ and $y_0$.

• The main objects of interest are the average treatment effect:

$$ATE = E(y_1 - y_0),$$

and the average treatment effect on the treated:

$$ATE_1 = E(y_1 - y_0 \mid \text{PE Buyout}),$$
Regression Approach (Tables 3-5)

• The nonparametric approach above does not control for target-control differences in performance prospects within industry-size-age-MU-year cells.

• Targets grow more slowly than controls in the year before buyout, which suggests that targets might be on a slower growth path in any event (even within cells).

• Do the results hold up when we condition on pre-buyout growth experience?
Regression Approach, 2

- A regression approach allows more flexibility in designing controls. In Table 3, the regression controls include fully interacted indicators for industry, firm age, firm size, MU status & year. We also include 2 controls for pre-buyout performance:
  - The employment growth rate from -3 to -1 for the set of establishments operated by the target firm in year 0.
  - The employment growth rate from t-3 to t-1 for the firm that owned the set of establishments in t-3. If ownership was split across multiple firms, we use the firm that accounts for the largest share of employment at these establishments (as of t-3).
Regression Approach, 3

• ATE=ATE1: the key independent variable is a dummy for whether the establishment is a PE target. The estimation method assumes a common treatment effect.

• ATE1 Heterogeneous: dummy is interacted with firm size, firm age, and pre-buyout performance variables.
  – More restrictive than the nonparametric specification in some respects but less restrictive in the inclusion of controls for pre-buyout growth history and in allowing treatment effect to vary with pre-buyout growth.
  – To recover average treatment effect on the treated in ATE1, we compute a weighted average of the heterogeneous estimated treatment effects, using cell-level employment weights of targets in the transaction year.
Semi-Parametric Regression Specifications

The ATE=ATE1 specification can be written

\[ Y_{i,t+j} = \alpha_j + \sum_c D_{cit} \theta_{c,j} + \lambda_{o,j} LFIRM_{it} + \lambda_{1,j} LEST_{it} + \gamma_j PE_{it} + \varepsilon_{i,t+j}, \]

where \( Y_{it} \) is the outcome variable (e.g., rate of growth, job creation, or job destruction) for firm \( i \) at time \( t+j \) for some \( j \in \{1,2,3,4,5\} \), \( D_{cit} \) is a set of dummy variables for cell \( c \) for firm \( i \) at time \( t \) where the cells are defined by the full cross product of buyout year \( t \), industry, firm size category, firm age category and multi-unit status, \( LFIRM_{it} \) is the growth rate from \( t-3 \) to \( t-1 \) of the parent firm as of \( t-3 \), \( LEST_{it} \) is the growth rate from \( t-3 \) to \( t-1 \) for the establishments that constitute the target firm in year \( t \), and \( PE_{it} \) is a dummy variable equal to 1 for a target firm.
Semi-Parametric Regression Specifications

The ATE1 Heterogeneous specification is

\[ Y_{i,t+j} = \alpha_j + \sum_c D_{cit} \theta_{c,j} + \lambda_{o,j} LFIRM_{it} + \lambda_{1,j} LEST_{it} \]

\[ + \sum_k D_{kit} PE_{it} \gamma_{k,j} + \gamma_{o,j} LFIRM_{it} PE_{it} + \gamma_{1,j} LEST_{it} PE_{it} + \varepsilon_{i,t+j} \]

All variables are defined as above, but the ATE1 heterogeneous specification allows the treatment effect to vary by characteristics including a set of cell-based variables \( k \) (in practice by firm size and by firm age – not interacted) and the lagged growth terms. To recover the average treatment effect on the treated in this case, we compute a weighted average of the heterogeneous estimated treatment effects, using cell-level employment weights of targets in the buyout year. We calculate standard errors by the Delta method.
Regression Approach, 4

• Each row in Table 3 (next slide) corresponds to a different regression. Weighting is based on the target establishment’s employment in the event year.

• Standard errors calculated by the Delta method.

Table 3. Post-Buyout Employment Growth Rates at Target Establishments Relative to Controls, Buyouts from 1980 to 2000

<table>
<thead>
<tr>
<th></th>
<th>Nonparametric Comparison From Figure 3b</th>
<th>Semi-Parametric Regressions</th>
<th></th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>ATE=ATE1</td>
<td>ATE1</td>
<td></td>
</tr>
<tr>
<td>Buyout Year</td>
<td>2.17</td>
<td>2.08 (0.17)</td>
<td>2.28 (0.17)</td>
<td></td>
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<tr>
<td>Buyout Year +1</td>
<td>-0.93</td>
<td>-0.72 (0.20)</td>
<td>-1.15 (0.20)</td>
<td></td>
</tr>
<tr>
<td>+2</td>
<td>-2.23</td>
<td>-1.74 (0.20)</td>
<td>-1.76 (0.21)</td>
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</tr>
<tr>
<td>+3</td>
<td>-0.55</td>
<td>0.00 (0.21)</td>
<td>0.08 (0.21)</td>
<td></td>
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<tr>
<td>+4</td>
<td>-1.64</td>
<td>-1.31 (0.22)</td>
<td>-1.16 (0.22)</td>
<td></td>
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<tr>
<td>+5</td>
<td>-1.09</td>
<td>-0.95 (0.22)</td>
<td>-1.23 (0.23)</td>
<td></td>
</tr>
<tr>
<td>Cumulative, Years 1 to 5</td>
<td>-6.44</td>
<td>-4.72 (0.22)</td>
<td>-5.22 (0.23)</td>
<td></td>
</tr>
</tbody>
</table>
• Consistent estimation of treatment effects requires conditional mean independence: 
  \[ E(y_0 \mid X, w) = E(y_0 \mid X) \text{ and } E(y_1 \mid X, w) = E(y_1 \mid X), \]
  where \( y_1 \) is the outcome with treatment, and \( w \) is a binary r.v. where \( w=1 \) denotes treatment.

• If \( w \) and \( (y_0, y_1) \) are statistically independent, conditional on \( X \), then conditional mean independence follows.

• Conditional independence is called “ignorability of treatment” in the treatment effects literature. See Sections 18.1 to 18.3 in Woolridge (2002).
Have We Identified Causal Effect ...?

• Conditional (mean) independence is a strong requirement. It fails if the outcome variable is correlated with the probability of being treated, conditional on the regression controls.

• Conditional independence is more plausible in our setting than in previous work on effects of PE buyouts because of our more extensive set of controls: randomness requirement is more likely to hold within industry-size-age-year cells than across these cells.

• But it’s still an issue.
Have We Identified Causal Effect...?

Other Identification Issues:

- The stable unit treatment value assumption (SUTVA) maintains that the treatment of one unit has no effect on outcomes at other units. This assumption could fail because of:
  - Standard general equilibrium effects, e.g., buyouts accelerate growth in targets, displacing controls.
  - Demonstration and imitation effects, e.g., controls observe successful innovations by targets and copy them.
Have We Identified Causal Effect ...?

Other Identification Issues:

• What’s the correct counterfactual for no buyout in year t?
  – A buyout in some later year?
  – Some other mechanism to effectuate a change in control or in operating performance by the target firm in year t or later?
  – Eventual failure of target absent a buyout?

• Perhaps it’s best to view our estimated effects as capturing outcomes that would have occurred eventually through some mechanism. Under this view, our results still imply that buyouts accelerate the reallocation of jobs and workers (and capital).
Taking Stock

• Employment falls more rapidly at target establishments than at controls post buyout
  – Higher job destruction, not lower job creation
• More pronounced employment declines (relative to controls) for public-to-private deals
• Little difference between targets and controls in Manufacturing, big difference in Retail and Services
• Thus far, the analysis ignores greenfield job creation – new jobs at new establishments opened post buyout.
Firm-Level Analysis

At the firm level, employment can change through:

– Job creation and destruction at establishments acquired in buy out
– Job creation at greenfield establishments opened post buyout
– Acquisitions and divestitures
Table 4. Buyout Effects on Employment Growth Rates at Target Firms Relative to Controls, Buyouts from 1980-2003

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Regression Specification</th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>ATE=ATE1</td>
<td>ATE1 Heterogeneous</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Buyout Effect</td>
<td>$R^2$</td>
<td>Buyout Effect</td>
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<tr>
<td>Firm-level Employment Growth Rate from</td>
<td>-0.88</td>
<td>0.07</td>
<td>-0.65</td>
</tr>
<tr>
<td>Buyout Year $t$ to $t+2$</td>
<td>(0.18)</td>
<td></td>
<td>(0.16)</td>
</tr>
<tr>
<td></td>
<td>By Adjustment Margin</td>
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<td></td>
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<tr>
<td>Continuers</td>
<td>-1.57</td>
<td>0.09</td>
<td>-1.36</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td></td>
<td>(0.11)</td>
</tr>
<tr>
<td>Creation</td>
<td>-1.07</td>
<td>0.16</td>
<td>-0.93</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td></td>
<td>(0.08)</td>
</tr>
<tr>
<td>Destruction</td>
<td>0.71</td>
<td>0.09</td>
<td>0.64</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td></td>
<td>(0.07)</td>
</tr>
<tr>
<td>Deaths</td>
<td>4.12</td>
<td>0.06</td>
<td>4.13</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td></td>
<td>(0.08)</td>
</tr>
<tr>
<td>Births</td>
<td>1.80</td>
<td>0.22</td>
<td>1.87</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td></td>
<td>(0.05)</td>
</tr>
<tr>
<td>Acquisitions</td>
<td>5.62</td>
<td>0.12</td>
<td>5.56</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td></td>
<td>(0.05)</td>
</tr>
<tr>
<td>Divestitures</td>
<td>2.77</td>
<td>0.06</td>
<td>2.75</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td></td>
<td>(0.04)</td>
</tr>
</tbody>
</table>
Hypothesis 1: PE acts as an agent of change – inducing some target firms to expand relative to controls and others to retrench.

Under this hypothesis, the foregoing evidence reflects a mix of (a) upsizing target firms that add establishments and jobs more rapidly than controls and (b) downsizing target firms that shed jobs and establishments more rapidly. Positive effects of buyouts on creation, destruction, acquisitions, and divestitures then result by aggregating over upsizing and downsizing cases.
Hypothesis 2: PE acts as an agent of restructuring within target firms, accelerating the reallocation of jobs across establishments in these firms and their pace of acquisition and divestment.

These hypotheses are not exclusive because private equity could accelerate both types of creative destruction.
Evidence Strongly Favors the Second View: PE Buyouts as Agents of Reallocation within Firms

Table 5: Buyout Effects on Firm-Level Excess Job Reallocation Rates over First Two Years Post Buyout, Buyouts form 1980 to 2003

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Regression Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ATE=ATE1</td>
</tr>
<tr>
<td></td>
<td>Buyout Effect, $R^2$</td>
</tr>
<tr>
<td>Firm-level Excess Reallocation – All Adjustment Margins</td>
<td>9.25, 0.37</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
</tr>
<tr>
<td>Firm-level Excess Reallocation – Births, Deaths &amp; Continuers</td>
<td>6.38, 0.38</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
</tr>
</tbody>
</table>

Excess Job Reallocation = Gross Job Creation + Gross Job Destruction – Absolute Value of Net Employment Change

Excess Job Reallocation Rate within Control Firms

- Organic Margins = 27%
- All Margins = 30%
Table 6: Cumulative Two-Year Job Reallocation at Target Firms And Controls, Buyouts from 1980 to 2003

A. Organic Changes, Excluding Acquisitions and Divestitures

<table>
<thead>
<tr>
<th>Rates Expressed as a Percent of Employment</th>
<th>Target Firms</th>
<th>Control Firms</th>
<th>Difference</th>
<th>From Tables 4 and 5</th>
<th>Difference</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job Creation</td>
<td>24.96</td>
<td>22.96</td>
<td>2.00</td>
<td></td>
<td>0.94</td>
<td>(0.10)</td>
</tr>
<tr>
<td><strong>Continuers</strong></td>
<td>11.51</td>
<td>11.74</td>
<td>-0.22</td>
<td>-0.93</td>
<td>(0.07)</td>
<td></td>
</tr>
<tr>
<td><strong>Deaths (Entrants)</strong></td>
<td>13.44</td>
<td>11.22</td>
<td>2.22</td>
<td>1.87</td>
<td>(0.05)</td>
<td></td>
</tr>
<tr>
<td>Job Destruction</td>
<td>26.89</td>
<td>22.62</td>
<td>4.27</td>
<td>4.69</td>
<td>(0.11)</td>
<td></td>
</tr>
<tr>
<td><strong>Continuers</strong></td>
<td>13.28</td>
<td>12.65</td>
<td>0.63</td>
<td>0.64</td>
<td>(0.06)</td>
<td></td>
</tr>
<tr>
<td><strong>Deaths (Exits)</strong></td>
<td>13.60</td>
<td>9.96</td>
<td>3.64</td>
<td>4.13</td>
<td>(0.08)</td>
<td></td>
</tr>
<tr>
<td>Employment Growth</td>
<td>-1.93</td>
<td>0.34</td>
<td>-2.27</td>
<td>-3.75</td>
<td>(0.16)</td>
<td></td>
</tr>
<tr>
<td>Job Reallocation</td>
<td>51.85</td>
<td>45.58</td>
<td>6.27</td>
<td>5.62</td>
<td>(0.14)</td>
<td></td>
</tr>
<tr>
<td>Excess Reallocation</td>
<td>49.91</td>
<td>45.23</td>
<td>4.68</td>
<td></td>
<td></td>
<td>(0.08)</td>
</tr>
<tr>
<td><strong>Within-Firm</strong></td>
<td>33.09</td>
<td>27.02</td>
<td>6.06</td>
<td>6.40</td>
<td>(0.08)</td>
<td></td>
</tr>
</tbody>
</table>

See paper for corresponding analysis of all adjustment margins, including acquisitions and divestitures.
Table 7. Buyout Effects on Target Firms Relative to Controls by Type of Buyout, 1980 to 2003

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Public to Private</th>
<th>Independent to Private</th>
<th>Divisional Buyout</th>
<th>Secondary Buyout</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment Growth Rate from Buyout Year ( t ) to ( t+2 )</td>
<td>-10.36 (0.42)</td>
<td>10.51 (0.24)</td>
<td>-1.47 (0.45)</td>
<td>7.15 (0.58)</td>
<td>-6.45 (0.80)</td>
</tr>
<tr>
<td>Excess Reallocation Rate from Buyout Year ( t ) to ( t+2 )</td>
<td>5.09 (0.24)</td>
<td>4.69 (0.10)</td>
<td>20.32 (0.19)</td>
<td>29.79 (0.27)</td>
<td>6.16 (0.40)</td>
</tr>
</tbody>
</table>

Number of Observations:
- Public to Private: 289,228
- Independent to Private: 1,269,396
- Divisional Buyout: 456,135
- Secondary Buyout: 168,508
- Other: 122,613

Notes:
1. Results are based on the semi-parametric ATE1 Heterogeneous specifications of Tables 4 and 5, fit separately to target and control observations for each type of private equity buyout.

Results by Type of Private Equity Buyout
1. Target-firm employment responses (relative to controls) vary greatly by type of PE buyout.
2. Excess job reallocation rates at target firms increase substantially in the wake of PE buyouts (relative to controls) for all buyout types.
Measuring Plant-Level TFP

\[ \ln TFP_{it} = \ln Q_{it} - \alpha_K \ln K_{it} - \alpha_L \ln L_{it} - \alpha_M \ln M_{it} \]

- Output = shipments + inventory change, deflated by industry-level price index
- Capital measured separately for equipment and structures by perpetual inventory methods
- Labor = total hours of all workers
- Energy and other materials measured and deflated separately
- Elasticities = cost shares in same year & industry (4-digit SIC or 6-digit NAICS)
### A. Plant Exit Probabilities in the First Two Years Post Buyout (Logistic Specification)

<table>
<thead>
<tr>
<th>Location in Own-Industry TFP Distribution as of the Buyout Year t</th>
<th>Probability of Plant Exit by Year t+2</th>
<th>P-value for Difference Between Targets and Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bottom Tercile</td>
<td>0.143 (0.023)</td>
<td>0.091 (0.002)</td>
</tr>
<tr>
<td>Middle Tercile</td>
<td>0.112 (0.034)</td>
<td>0.062 (0.002)</td>
</tr>
<tr>
<td>Top Tercile</td>
<td>0.078 (0.015)</td>
<td>0.067 (0.002)</td>
</tr>
</tbody>
</table>

### B. Plant Entry Probabilities in the First Two Years Post Buyout (Logistic Specification)

<table>
<thead>
<tr>
<th>Location in Own-Industry TFP Distribution in t+2, Two Years After Buyout</th>
<th>Probability that a Plant Operating in t+2 Entered in t+1 or t+2</th>
<th>P-value for Difference Between Targets and Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bottom Tercile</td>
<td>0.056 (0.015)</td>
<td>0.121 (0.006)</td>
</tr>
<tr>
<td>Middle Tercile</td>
<td>0.071 (0.016)</td>
<td>0.078 (0.003)</td>
</tr>
<tr>
<td>Top Tercile</td>
<td>0.127 (0.029)</td>
<td>0.072 (0.003)</td>
</tr>
</tbody>
</table>

Logistic regressions with propensity weights to adjust for sampling
Table 9: Productivity of Target and Control Plants, Buyouts in Manufacturing from 1980 to 2003

A. TFP In Buyout Year $t$ by Plant Status in Year $t+2$

<table>
<thead>
<tr>
<th>Plant Status</th>
<th>Targets</th>
<th>Controls</th>
<th>P-Value for Difference Between Targets and Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continuers</td>
<td>0.016</td>
<td>Omitted Group</td>
<td>0.180</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exits</td>
<td>-0.075</td>
<td>-0.032</td>
<td>0.232</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>Divestitures</td>
<td>-0.023</td>
<td>-0.044</td>
<td>0.462</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.538</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:**
- OLS regressions with propensity weights set to reciprocal of model-implied sample-inclusion probabilities
- Specifications include industry-year effects and firm size and age effects
- Sample of about 107,000 establishments, including 2,050 targets.
Table 9: Productivity of Target and Control Plants, Buyouts in Manufacturing from 1980 to 2003

<table>
<thead>
<tr>
<th>Plant Status</th>
<th>Targets</th>
<th>Controls</th>
<th>P-Value for Difference Between Targets and Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continuers</td>
<td>0.020</td>
<td>Omitted Group</td>
<td>0.076</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entrants</td>
<td>0.182</td>
<td>-0.039</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.011)</td>
<td></td>
</tr>
<tr>
<td>Acquisitions</td>
<td>-0.010</td>
<td>-0.030</td>
<td>0.668</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.523</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Productivity of Target and Control Plants, Buyouts in Manufacturing from 1980 to 2003

Table 9

<table>
<thead>
<tr>
<th>C. TFP Growth at Continuing Plants, from Buyout Year $t$ to $t+2$</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable: Change in Plant-level Log TFP from Buyout Year $t$ to $t+2$</td>
<td>Targets</td>
<td>Controls</td>
</tr>
<tr>
<td>Continuers</td>
<td>0.001 (0.011)</td>
<td>Omitted Group</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.071</td>
<td></td>
</tr>
</tbody>
</table>

No discernable difference between continuing target and control plants in post-buyout TFP growth.
Overall TFP Effect: Putting the Pieces Together

Consider the difference-in-difference $\Delta P_t - \Delta \tilde{P}_t$, where

$$\Delta P_t = \left[ S_{t+2}^C P_{t+2}^C - S_t^C P_t^C \right] + \left[ S_{t+2}^N P_{t+2}^N - S_t^X P_t^X \right] + \left[ S_{t+2}^A P_{t+2}^A - S_t^D P_t^D \right]$$

is the average two-year change in TFP among target firms, and

- $S$ denotes an employment share,
- $P$ denotes a TFP value
- $C, N, X, A$ and $D$ denote continuers, entrants, exits, acquisitions, and divestitures, respectively.

For example, $P_{t+2}^C$ is the average TFP among continuing target plants two years post buyout, where each plant’s TFP is expressed as a deviation from mean log TFP in the same industry-year cell. Define $\Delta \tilde{P}_t$ for controls firms analogously.
New Decomposition of TFP Changes

Now express the TFP terms as deviations about same-year TFP values for control continuers, cancel terms in $\Delta P_t - \Delta \tilde{P}_t$, and rearrange to obtain:

$$\Delta P_t - \Delta \tilde{P}_t = S_{t+2}^C \left( P_{t+2}^C - \tilde{P}_{t+2}^C \right) - S_t^C \left( P_t^C - \tilde{P}_t^C \right)$$

$$+ S_{t+2}^N \left( P_{t+2}^N - \tilde{P}_{t+2}^N \right) - \tilde{S}_{t+2}^N \left( \tilde{P}_{t+2}^N - \tilde{P}_{t+2}^C \right) - S_t^X \left( P_t^X - \tilde{P}_t^X \right) + \tilde{S}_t^X \left( \tilde{P}_t^X - \tilde{P}_t^C \right)$$

$$+ S_{t+2}^A \left( P_{t+2}^A - \tilde{P}_{t+2}^C \right) - \tilde{S}_{t+2}^A \left( \tilde{P}_{t+2}^A - \tilde{P}_{t+2}^C \right) - S_t^D \left( P_t^D - \tilde{P}_t^D \right) + \tilde{S}_t^D \left( \tilde{P}_t^D - \tilde{P}_t^C \right)$$

The “S” terms in this decomposition follow from the manufacturing analog to Table 6. The terms in parentheses can be read directly from the diff-in-diff estimates in Table 9.
Attractive Features of the TFP Change Decomposition

1. It shows how to combine diff-in-diff estimates of PE effects with a simple accounting relationship often used in research on firm-level productivity dynamics.

2. The decomposition sidesteps any need to compare TFP across industries or years – all productivity terms involve plant-level TFP deviations about same industry-year means.
Overall Effects of Buyouts on TFP Growth

Table 10. Impact of Private Equity Buyouts on Total Factor Productivity in the Manufacturing Sector, Buyouts from 1980 to 2003

Estimated Average Two-Year Post-Buyout Change in TFP at Target Firms Relative to Controls, Log Points

<table>
<thead>
<tr>
<th>TFP Log Change Differential</th>
<th>2.14</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excluding Acquisitions &amp; Divestitures</td>
<td>2.01</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Share of Total TFP Two-Year Change Differential By Margin of Adjustment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continuing Establishments</td>
</tr>
<tr>
<td>Entry and Exit</td>
</tr>
<tr>
<td>Acquisitions and Divestitures</td>
</tr>
</tbody>
</table>

Baseline TFP growth for control continuers = -0.38
Sources of TFP Gains: Reallocation Direction vs. Intensity

For additional insight into the nature of the entry and exit effects, we replace $S^N$ and $\tilde{S}^N$ with their average in (1), do the same for $S^X$ and $\tilde{S}^X$, and then recalculate the second line of (1) to obtain a value of 1.56 log points. This calculation corresponds to a counterfactual that turns off target-control differences in the pace of job reallocation to isolate the role of differences in its direction. The message is clear: The stronger directedness of job reallocation in target firms accounts for almost all of the entry and exit contribution to (1) and, indeed, more than 70 percent of $\Delta P_t - \Delta \tilde{P}_t$. 
Sources of TFP Gains:
Reallocation Direction vs. Intensity

Two other remarks help put this finding in perspective. First, while directional differences are central to our explanation for superior TFP growth at target firms, they matter because entry and exit involve sizable rates of job creation and destruction. In this respect, both the pace of job reallocation and the target-control directional differences are essential. Second, reallocation rates are considerably higher outside the manufacturing sector, as readily seen by comparing Tables 6 and C.2. This fact has potentially important implications for the TFP effects of buyouts in the private sector as a whole. If we plug private sector share values from Table 6 into (1) alongside diff-in-diff estimates from Table 9, the implied TFP growth advantage of targets is 3.05 log points, 81 percent of which is due to entry and exit effects.
PE Buyout Effects on Earnings Per Worker

Buyout targets also divest establishments with high EPW (relative to control continuers), whereas controls do not.

Applying above decomposition to EPW results reveals that unit labor input costs decline by 4.0 log points for target firms (relative to control firms) over two years post buyout, mainly due to EPW reductions at continuing establishments and secondarily due to greater propensity to divest high EPW establishments.
Summary of Results and Conclusions

1. Employment shrinks more rapidly at target establishments than at controls after buyout
   
   A. Big gap – about 3% of base employment over two years and 6% over five years
   
   B. Higher job destruction, not lower job creation
      
      • Gross destruction at targets outpaces job destruction at controls by a cumulative 10 percentage points over 5 years.
      
      • So jobs at target establishments are at greater risk of disappearing in the wake of buyouts.

_But_, that’s not the full story ...
2. Target firms destroy more jobs post buyout, and they create more new jobs (mostly at new facilities), both at a higher rate than controls. Overall net employment effects are modest.

- Accounting for all adjustment margins, the net growth differential between target and control firms is less than 1% of initial employment over two years (in favor of controls)

- Alternatively, adjusting the employment growth differential from the establishment-level analysis for target firms’ greater job creation at births, the net growth differential is slightly over 1% of initial employment over two years (in favor of controls)
3. **PE Buyouts have large effects on the gross creation and destruction of jobs:**

   - The job reallocation rate at target firms exceeds that of controls by 14 percentage points over 2 years post buyout.
   - About 45% of this extra job reallocation reflects a more rapid pace of organic employment adjustments, and the rest reflects acquisitions and divestitures.

4. **Private equity acts as an agent of restructuring in the sense that buyouts accelerate the reallocation of jobs across establishments *within* target firms.**
5. Employment responses to PE buyouts vary considerably across industries and by type of transactions.

- Looking across industries, the largest losses at targets relative to controls occur in Retail Trade.
- Public-to-private deals, which tend to be highly visible, involve large employment losses at targets relative to controls.
- In contrast, independently owned firms exhibit large employment gains relative to controls in the wake of buyouts, mainly due to greater acquisitions.
  - PE buyouts of independents are more numerous than public-to-private transactions, and they account for a larger share of jobs.
6. Private equity buyouts increase TFP growth (results for manufacturing only).

– TFP growth rate rises by about 2 percentage points over two years at target firms relative to controls over the first two years post buyout

– Three-quarters the TFP growth effect works through plant entry and exit margins – i.e., PE more aggressively shuts down low-productivity plants and opens more high-productivity plants.

– The main source of superior TFP performance for target firms involves the effects of PE on the direction of job reallocation. The differential target-control effect on the pace of reallocation makes a much smaller contribution.
7. Private equity buyouts reduce earnings per worker (EPW)
   - EPW declines by about 4% at target firms relative to controls over two years post buyout.
   - EPW effect works mainly through declines at continuing establishments, secondarily through a greater propensity of target firms to divest high EPW establishments.

8. PE buyout effects on EPW are strongly negative in Wholesale, Retail, and Services, industries that rely heavily on less skilled labor.
   - EPW effects are small in Manufacturing, and large and positive in FIRE.
9. Large positive effects (on average) of PE buyouts on net operating margins at target firms:

- TFP results $\rightarrow$ buyouts improve operating margins by about 2 percentage points over two years
- Earnings per worker results $\rightarrow$ wage reductions lower unit costs by another 2 percentage points, assuming a 50% labor cost share

$\rightarrow$ Operating margins improve by about 4 percentage points (mixing manufacturing and private sector results)
- Resulting profitability gains are magnified in their effect on earning per share by levered capital structures at buyout targets
Two Alternative Views Circa 2006:

- Secularly rising volatility of growth rates in sales and employment among publicly traded firms – sometimes taken as a characterization of all firms.
- Secularly rising variance in the idiosyncratic component of firm-level equity returns
- Secularly declining excess job reallocation rates and declining rates of business entry and exit.
- There is considerable tension between these views
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.

• 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

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

Average Volatility of Sales Growth Rates

Simple Mean

Sales-weighted mean
Figure 1(b): Volatility, Publicly Traded Firms

Based on COMPUSTAT Data

Average Volatility of Employment Growth Rates

Simple Mean

Employment-weighted mean

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

LRD data spliced to other sources.
Based on data from the BLS Business Employment Dynamics
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
  – 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:

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

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

where $\alpha_{i}$ 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

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)

- GDP
- Durable Goods Output
- Residential Investment
- Inventory Investment

Reproduced from Davis And Kahn, 2008 JEP
Overview of Davis et al. 2006 Paper


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 2010)
- **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
• 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
Employment-weighted correlation = 0.83

Weighted Mean Absolute Difference = 30%

Source: Own Calculations from Compustat/LBD
Compustat to Business Register 5-year Growth in Employment

Weighted Corr. = 0.54

Source: Own Calculations from Compustat/LBD
Figure 3: Full COMPSTAT Compared to Bridge Cases

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

<table>
<thead>
<tr>
<th>Year</th>
<th>Compustat, Unweighted</th>
<th>Bridge, Unweighted</th>
<th>Compustat, Weighted</th>
<th>Bridge, Weighted</th>
</tr>
</thead>
<tbody>
<tr>
<td>1954</td>
<td>0.07</td>
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<tr>
<td>1959</td>
<td>0.07</td>
<td></td>
<td>0.09</td>
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<tr>
<td>1964</td>
<td>0.11</td>
<td></td>
<td>0.11</td>
<td></td>
</tr>
<tr>
<td>1969</td>
<td>0.11</td>
<td></td>
<td>0.13</td>
<td></td>
</tr>
<tr>
<td>1974</td>
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<td></td>
<td>0.15</td>
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<tr>
<td>1979</td>
<td>0.15</td>
<td></td>
<td>0.15</td>
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</tr>
<tr>
<td>1984</td>
<td>0.15</td>
<td></td>
<td>0.15</td>
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<tr>
<td>1989</td>
<td>0.15</td>
<td></td>
<td>0.15</td>
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<tr>
<td>1994</td>
<td>0.15</td>
<td></td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td>1999</td>
<td>0.15</td>
<td></td>
<td>0.15</td>
<td></td>
</tr>
</tbody>
</table>
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

Firm Level Volatility - - Cross Sectional Dispersion (right axis)
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

<table>
<thead>
<tr>
<th>Year</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1977</td>
<td></td>
</tr>
<tr>
<td>1980</td>
<td></td>
</tr>
<tr>
<td>1983</td>
<td></td>
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<td>1986</td>
<td></td>
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<tr>
<td>1989</td>
<td></td>
</tr>
<tr>
<td>1992</td>
<td></td>
</tr>
<tr>
<td>1995</td>
<td></td>
</tr>
<tr>
<td>1998</td>
<td></td>
</tr>
<tr>
<td>2001</td>
<td></td>
</tr>
</tbody>
</table>

Legend:
- Green line: Total
- Pink line: Privately Held
- Black line: Publicly Traded
Figure 5: Average Volatility of Employment Growth Rate by Ownership Status, LBD Data
Modified Volatility Measure, Allow the Window Length to Vary

\[ \tilde{\sigma}_{it} = \left[ \sum_{\tau=-4}^{5} \left( \frac{\tilde{Z}_{i,t+\tau}}{P_{it}} - 1 \right) (\gamma_{i,t+\tau} - \overline{\gamma}_{it}^w)^2 \right]^{1/2} \]
# of years from $t-4$ to $t+5$ for which $z_{it} > 0$.

$$z_{it} = \frac{1}{2} \left( x_{it} + x_{it-1} \right)$$

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

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

$$\widehat{Z}_{it} = K_{it} z_{it}$$

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

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

Correcting a typo in the paper.
Figure 6: Modified Volatility by Ownership Status

Modified Volatility, Employment Weighted

Year

Average Firm Volatility


129
Table 2: Industry Level Outcomes, Modified Volatility Measure

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Minerals</td>
<td>0.54</td>
<td>0.41</td>
<td>-24.2</td>
<td>0.25</td>
<td>0.28</td>
<td>10.9</td>
<td>0.74</td>
<td>0.52</td>
<td>-29.8</td>
<td>3.0</td>
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<td>-1.1</td>
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<tr>
<td>Construction</td>
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<td>0.51</td>
<td>-34.5</td>
<td>0.33</td>
<td>0.34</td>
<td>1.3</td>
<td>0.82</td>
<td>0.52</td>
<td>-36.6</td>
<td>2.5</td>
<td>1.5</td>
<td>-0.9</td>
</tr>
<tr>
<td>Manufacturing</td>
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<td>0.30</td>
<td>-12.9</td>
<td>0.16</td>
<td>0.21</td>
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<td>1.7</td>
<td>-1.5</td>
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<tr>
<td>TPU</td>
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<td>0.34</td>
<td>-6.7</td>
<td>0.11</td>
<td>0.25</td>
<td>129.4</td>
<td>0.67</td>
<td>0.45</td>
<td>-32.8</td>
<td>6.3</td>
<td>1.8</td>
<td>-4.4</td>
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<tr>
<td>Wholesale</td>
<td>0.53</td>
<td>0.33</td>
<td>-36.5</td>
<td>0.16</td>
<td>0.24</td>
<td>45.6</td>
<td>0.58</td>
<td>0.36</td>
<td>-38.3</td>
<td>3.6</td>
<td>1.5</td>
<td>-2.1</td>
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<tr>
<td>Retail</td>
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<td>-36.1</td>
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<td>0.20</td>
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<td>0.70</td>
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<td>-37.5</td>
<td>4.2</td>
<td>2.2</td>
<td>-1.9</td>
</tr>
<tr>
<td>FIRE</td>
<td>0.44</td>
<td>0.39</td>
<td>-13.1</td>
<td>0.17</td>
<td>0.33</td>
<td>96.4</td>
<td>0.54</td>
<td>0.42</td>
<td>-22.6</td>
<td>3.3</td>
<td>1.3</td>
<td>-2.0</td>
</tr>
<tr>
<td>Services</td>
<td>0.59</td>
<td>0.41</td>
<td>-30.7</td>
<td>0.27</td>
<td>0.38</td>
<td>38.5</td>
<td>0.61</td>
<td>0.41</td>
<td>-32.4</td>
<td>2.3</td>
<td>1.1</td>
<td>-1.2</td>
</tr>
<tr>
<td>All</td>
<td>0.49</td>
<td>0.38</td>
<td>-22.9</td>
<td>0.17</td>
<td>0.26</td>
<td>55.5</td>
<td>0.63</td>
<td>0.42</td>
<td>-33.4</td>
<td>3.7</td>
<td>1.6</td>
<td>-2.1</td>
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</table>
### (Basic) Firm-Level Volatility, 1982-1996, Percent Change by Industry

<table>
<thead>
<tr>
<th>Industry</th>
<th>1982</th>
<th>1996</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minerals</td>
<td>0.24</td>
<td>0.15</td>
<td>-39</td>
</tr>
<tr>
<td>Const.</td>
<td>0.45</td>
<td>0.22</td>
<td>-52</td>
</tr>
<tr>
<td>Manuf.</td>
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<td>0.08</td>
<td>-38</td>
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<tr>
<td>TPU</td>
<td>0.18</td>
<td>0.10</td>
<td>-44</td>
</tr>
<tr>
<td>Wholesale</td>
<td>0.24</td>
<td>0.11</td>
<td>-53</td>
</tr>
<tr>
<td>Retail</td>
<td>0.19</td>
<td>0.10</td>
<td>-46</td>
</tr>
<tr>
<td>FIRE</td>
<td>0.18</td>
<td>0.14</td>
<td>-23</td>
</tr>
<tr>
<td>Services</td>
<td>0.29</td>
<td>0.14</td>
<td>-53</td>
</tr>
</tbody>
</table>
## (Basic) Volatility Convergence

<table>
<thead>
<tr>
<th>Industry</th>
<th>1982</th>
<th>1996</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minerals</td>
<td>4.5</td>
<td>1.4</td>
<td>-3.1</td>
</tr>
<tr>
<td>Const.</td>
<td>6.4</td>
<td>2.8</td>
<td>-3.6</td>
</tr>
<tr>
<td>Manuf.</td>
<td>3.7</td>
<td>1.7</td>
<td>-2.0</td>
</tr>
<tr>
<td>TPU</td>
<td>3.9</td>
<td>2.0</td>
<td>-1.9</td>
</tr>
<tr>
<td>Wholesale</td>
<td>2.9</td>
<td>1.5</td>
<td>-1.4</td>
</tr>
<tr>
<td>Retail</td>
<td>3.3</td>
<td>2.1</td>
<td>-1.3</td>
</tr>
<tr>
<td>FIRE</td>
<td>3.2</td>
<td>1.2</td>
<td>-2.1</td>
</tr>
<tr>
<td>Services</td>
<td>1.7</td>
<td>1.0</td>
<td>-0.7</td>
</tr>
</tbody>
</table>
## Figure 7: Dispersion of Establishment Growth Rates

### Employment-Weighted Dispersion of Establishment Growth Rates, Three-Year Moving Averages

<table>
<thead>
<tr>
<th>Year</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1977</td>
<td>0.5</td>
</tr>
<tr>
<td>1980</td>
<td>0.55</td>
</tr>
<tr>
<td>1983</td>
<td>0.6</td>
</tr>
<tr>
<td>1986</td>
<td>0.65</td>
</tr>
<tr>
<td>1989</td>
<td>0.7</td>
</tr>
<tr>
<td>1992</td>
<td>0.75</td>
</tr>
<tr>
<td>1995</td>
<td>0.8</td>
</tr>
<tr>
<td>1998</td>
<td>0.75</td>
</tr>
<tr>
<td>2001</td>
<td>0.6</td>
</tr>
</tbody>
</table>

- **Total**
- **Privately Held**
- **Publicly Traded**
Figure 7: Modified Volatility of Establishment Growth Rates

Modified Establishment Volatility, Employment Weighted
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 were 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

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>Entrants</td>
<td>1.6</td>
<td>1.2</td>
<td>1.47</td>
<td>1.63</td>
<td>11.0</td>
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<tr>
<td>1</td>
<td>3.4</td>
<td>2.6</td>
<td>1.36</td>
<td>1.37</td>
<td>1.3</td>
</tr>
<tr>
<td>2</td>
<td>4.3</td>
<td>3.4</td>
<td>1.21</td>
<td>1.14</td>
<td>-5.2</td>
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<tr>
<td>3</td>
<td>4.8</td>
<td>3.3</td>
<td>1.00</td>
<td>0.90</td>
<td>-9.5</td>
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<tr>
<td>4</td>
<td>4.3</td>
<td>3.0</td>
<td>0.84</td>
<td>0.79</td>
<td>-5.9</td>
</tr>
<tr>
<td>5</td>
<td>6.0</td>
<td>3.0</td>
<td>0.66</td>
<td>0.65</td>
<td>-1.2</td>
</tr>
<tr>
<td>6+</td>
<td>75.6</td>
<td>83.6</td>
<td>0.47</td>
<td>0.38</td>
<td>-20.8</td>
</tr>
<tr>
<td>Overall</td>
<td></td>
<td></td>
<td>0.60</td>
<td>0.48</td>
<td>-20.2</td>
</tr>
</tbody>
</table>

Statistics for 2001:
- Percent of Employment
  - 6-9 years: 10.2
  - 10-14 years: 11.1
  - 15-19 years: 11.6
  - 20-24 years: 10.2
  - 25+ years: 40.5
- Firm Volatility
  - 6-9 years: 0.45
  - 10-14 years: 0.37
  - 15-19 years: 0.32
  - 20-24 years: 0.30
  - 25+ years: 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

<table>
<thead>
<tr>
<th>Time Interval</th>
<th>Initial Volatility $\times 100$</th>
<th>Change in Volatility $\times 100$</th>
<th>Percentage of Volatility Change Accounted for by Cohort Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>1951-1978</td>
<td>8.87</td>
<td>2.03</td>
<td>49.1</td>
</tr>
<tr>
<td>1951-1999</td>
<td>8.87</td>
<td>7.14</td>
<td>59.4</td>
</tr>
<tr>
<td>1951-2004</td>
<td>8.87</td>
<td>4.55</td>
<td>90.0</td>
</tr>
<tr>
<td>1978-1999</td>
<td>10.89</td>
<td>5.11</td>
<td>63.5</td>
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<td>1978-2001</td>
<td>10.89</td>
<td>4.67</td>
<td>67.4</td>
</tr>
<tr>
<td>1978-2004</td>
<td>10.89</td>
<td>2.52</td>
<td>122.9</td>
</tr>
</tbody>
</table>
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.
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


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.


4. For more on the Great Moderation, see Davis and Kahn (2008) and references therein.