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

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1 Introduction

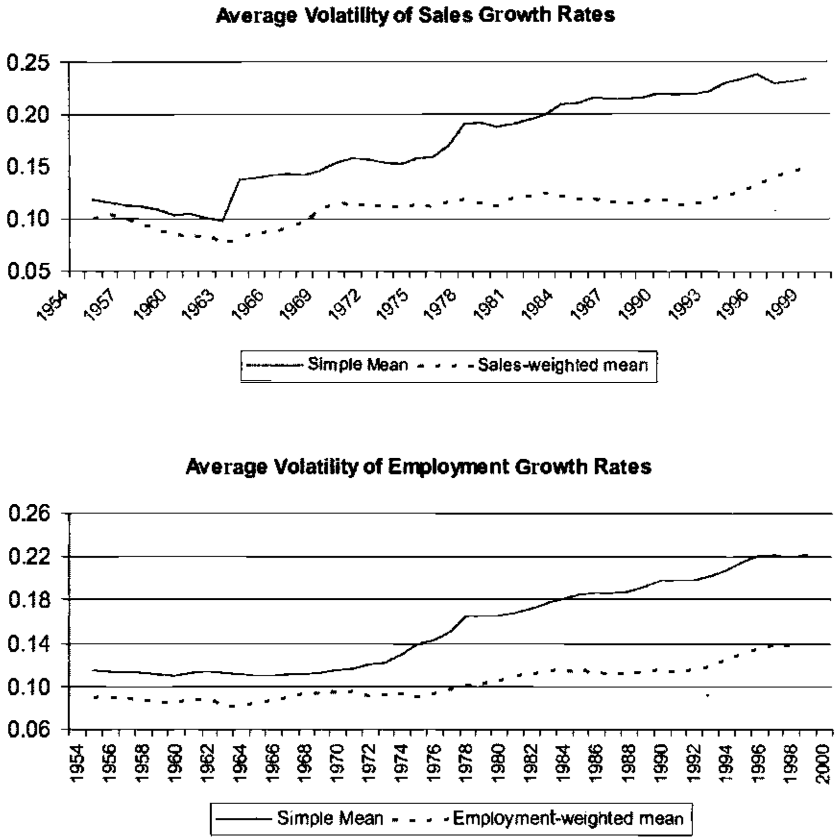
We study the variability of business growth rates in the U.S. economy from 1976 onwards. To carry out our study, we exploit the recently developed Longitudinal Business Database (LBD) (Jarmin and Miranda 2002a), which contains annual observations on employment and payroll for all establishments and firms in the private sector. Compared to other longitudinal business databases for the United States, the LBD is unparalleled in its comprehensive coverage over an extended period of time. The underlying sources for the LBD are periodic business surveys conducted by the Census Bureau and federal government administrative records.[1]

Macroeconomists increasingly recognize the importance of interactions between aggregate economic performance and the volatility and heterogeneity of business level outcomes. Idiosyncratic shocks are central to modern theories of unemployment. Frictions in product, factor and credit markets that impede business responses to idiosyncratic shocks can raise unemployment, lower productivity and depress investment. Financial innovations that facilitate better risk sharing can simultaneously encourage risk taking and investment, amplify business level volatility, and promote growth. Several recent studies hypothesize a close connection between declining aggregate volatility and trends in business level volatility. These examples of interactions between business level and aggregate outcomes help motivate our empirical study. Our chief objective is to develop a robust set of facts about the magnitude and evolution of business level volatility and the cross sectional dispersion of business growth rates in the U.S. economy.

Previous empirical work in this area yields an unclear picture. Several recent studies find a secular rise in average volatility among publicly traded firms. Examples include Campbell et al. (2001), Chaney, Gabaix, and Philippon (2002), Comin and Mulani (2006), and Comin and Philippon (2005). In figure 2.1, we replicate a key finding from the latter two studies. The figure shows that the average magnitudes of firm level volatility in the growth rates of sales and employment have roughly doubled since the early 1960s.[2] In a different line of research, Davis, Faberman, and Haltiwanger (2006) and Faberman (2006) produce evidence of a downward trend in the excess job reallocation rate, a measure of cross sectional dispersion in establishment growth rates.[3] As seen in the top panel of figure 2.2, the quarterly excess job reallocation rate in the U.S. manufacturing sector fell from about 12 percent in the early 1960s to 8 percent by 2005. The shorter time series in the lower panel shows a decline in excess job reallocation for the U.S. private sector from 16 percent or more in the early 1990s to less than 14 percent by 2005.[4] The data underlying figure 2.2 are not restricted to publicly traded firms.

There is an unresolved tension between the evidence of rising firm level volatility and declining cross sectional dispersion in establishment growth rates. To appreciate the tension, consider a simple example in which all employers follow identical and independent autoregressive processes. Then an increase in the innovation variance of idiosyncratic shocks implies an increase in employer volatility *and* in the cross sectional dispersion of growth rates. Of course, it is possible to break the tight link between employer volatility and cross sectional dispersion in more complicated specifications. It is also possible that firm and establishment growth processes have evolved along sharply different paths in recent decades. Yet another possibility is that the restriction to publicly traded businesses in previous studies paints a misleading picture of firm level volatility trends in the economy as a whole.[5] A related possibility is that the economic selection process governing entry into the set of publicly traded firms has changed over time in ways that affect measured trends in volatility.

In what follows, we explore each of these issues. We find similar trends in cross sectional dispersion and firm level volatility, so the different measures cannot account for the contrast between figures 2.1 and 2.2. Instead, the resolution turns mainly on the distinction between publicly traded and privately held businesses. For the private nonfarm sector as a whole, both firm level volatility and cross sectional dispersion



Source: Own calculations on COMPUSTAT data.

Notes: Calculations exclude entry and exit. Firm-level volatility calculated according to equation (5).

Figure 2.1
Firm Level Volatility for Publicly Traded Firms, COMPUSTAT Data

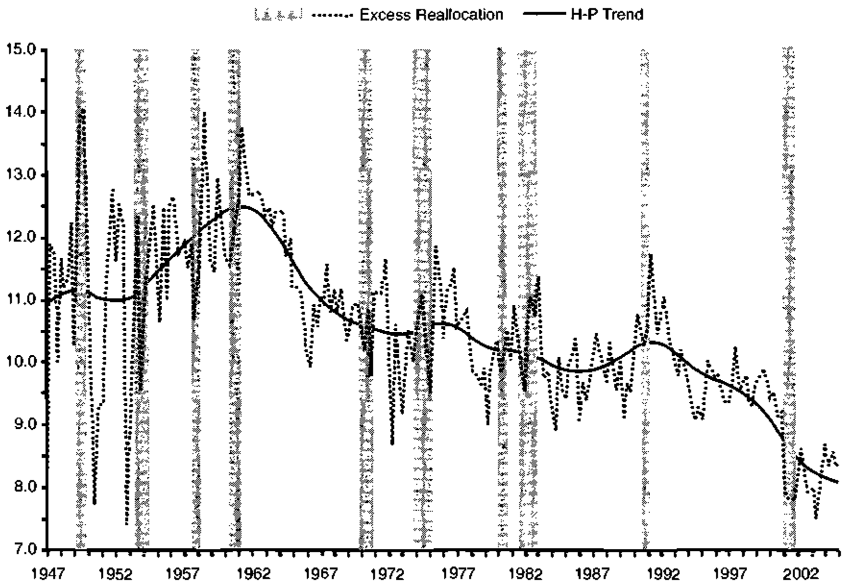
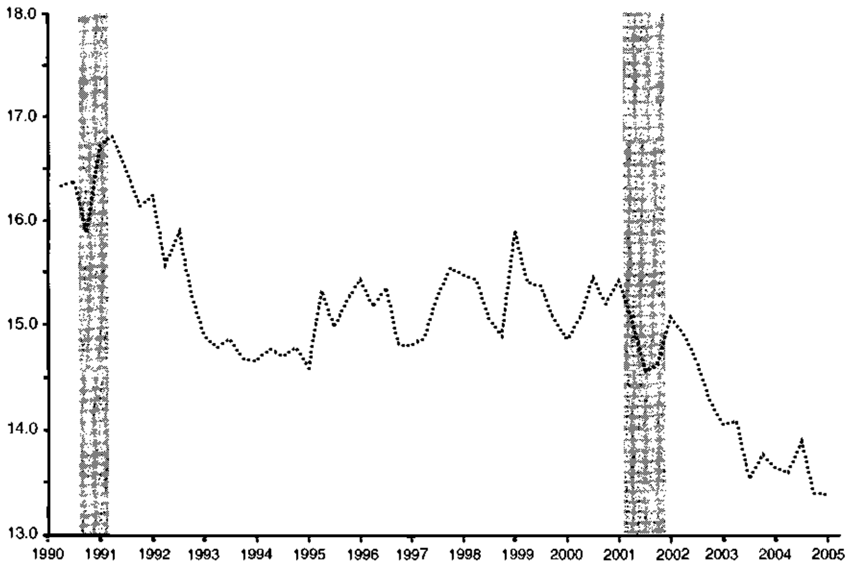


Figure 2.2a
Quarterly Excess Job Reallocation Rate, U.S. Manufacturing, 1947–2005



Source: Davis, Faberman, and Haltiwanger (2006) and Faberman (2006).

Figure 2.2b
Quarterly Excess Job Reallocation Rate, U.S. Private Sector, 1990–2005

measures show large declines in recent decades. For publicly traded firms, we provide independent evidence that cross sectional dispersion and firm level volatility have risen during the period covered by the LBD. We also show, however, that this rise for publicly traded firms is overwhelmed by the dramatic decline among privately held firms, which account for more than two-thirds of private business employment. Very similar results obtain when we treat establishments, rather than firms, as the unit of observation.

Two basic patterns hold across major industry groups. First, the volatility and dispersion of business growth rates are considerably greater for privately held firms. As of 1978, the average standard deviation of firm-level employment growth rates is 3.7 times larger for privately held than for publicly traded firms. This volatility ratio ranges from 2.3 in Services to 6.3 in Transportation and Public Utilities. Second, volatility and dispersion decline sharply among privately held businesses in the period covered by the LBD, and they rise sharply among publicly traded firms. The overall private-public volatility ratio falls to 1.6 by 2001, and it drops sharply in every major industry group. We refer to this phenomenon as "volatility convergence."

We also provide proximate explanations for these patterns. First, much of the decline in dispersion and volatility for the private sector as a whole, and for privately held firms in particular, reflects a decline in (employment-weighted) business entry and exit rates. Second, the age distribution of employment among privately held firms shifted towards older businesses in the period covered by the LBD. Because volatility declines steeply with age, the shift toward older businesses brought about a decline in overall volatility. We estimate that 27 percent or more of the volatility decline among privately held firms reflects the shift toward older businesses. Third, the evolution toward larger firms in certain industries, especially Retail Trade, accounts for about 10 percent of the volatility decline among nonfarm businesses during the period covered by the LBD.

Fourth, and perhaps most striking, changes over time in the number and character of newly listed firms played a major role in the volatility rise among publicly traded firms and in the volatility convergence phenomenon. There was a large influx of newly listed firms after 1979, and newly listed firms are much more volatile than seasoned listings. Moreover, firms newly listed in the 1980s and 1990s exhibit much greater volatility than earlier cohorts. Indeed, simple cohort dummies for the year of first listing in COMPUSTAT account for 67 percent of the volatility rise among publicly traded firms from 1978 to 2001, and they account for 90 percent of the smaller rise over the 1951–2004 period spanned by COMPUSTAT. Other evidence discussed below also points to important changes over time in the selection of firms that become public.

The paper proceeds as follows. Section 2 reviews the role of idiosyncratic shocks, producer heterogeneity and risk-taking in selected theories of growth, fluctuations and unemployment. Section 2 also identifies several factors that influence business volatility and its connection to aggregate volatility. Section 3 describes our data and measurement procedures. Section 4 presents our main empirical findings on volatility and cross sectional dispersion in business outcomes. Section 5 explores various factors that help to amplify and explain our main findings. Section 6 offers concluding remarks.

2 Conceptual Underpinnings and Theoretical Connections

Theories of growth and fluctuations in the Schumpeterian mold envision a market economy constantly disturbed by technological and commercial innovations. Firms and workers differ in their capacities to create, adopt and respond to these innovations, so that winners and losers emerge as unavoidable by-products of economic progress. According to this view, an economy's long-term growth rate depends on how well it facilitates and responds to the process of creative destruction (Aghion and Howitt 1998). Institutions and policies that impede restructuring and adjustment can mute the disruptive nature of factor reallocation—at the cost of lower productivity, depressed investment and, in some circumstances, persistently high unemployment (Caballero 2006).

Empirical evidence supports the Schumpeterian view in its broad outlines. Large-scale job reallocation is a pervasive feature of market economies (Davis and Haltiwanger 1999). The large job flows and high firm level volatility reflect the restructuring, experimentation and adjustment processes at the heart of Schumpeterian theories. Empirically, gross job flows are dominated by reallocation within narrowly defined sectors, even in countries that undergo massive structural transformations. Thus longitudinal firm and establishment data are essential for helping gauge the pace of restructuring and reallocation. Empirical studies also find that excess job reallocation rates decline strongly during the early lifecycle of firms and establishments (Davis and Haltiwanger (1992), and Bartelsman, Haltiwanger, and Scarpetta

(2004)). This finding indicates that experimentation and adjustment in the face of uncertainty about demand, technologies, costs, and managerial ability are especially pronounced among younger businesses.

A closely related empirical literature highlights the role of factor reallocation in productivity growth. Over horizons of five or ten years, the reallocation of inputs and outputs from less to more productive business units typically accounts for a sizable fraction of industry-level productivity growth (Foster, Haltiwanger, and Krizan 2001). Several studies reviewed in Caballero (2006, chapter 2) provide evidence that trade barriers, entry barriers, impediments to labor mobility, and misdirected financing can hamper efficient factor reallocation and, as a result, retard restructuring and undermine productivity growth. In short, there are sound theoretical and empirical reasons to treat restructuring and factor reallocation as key aspects of growth and fluctuations. The business volatility and dispersion measures that we construct in this study capture the pace of restructuring and reallocation on important dimensions. In this respect, they are useful inputs into theories of growth and fluctuations in the Schumpeterian mold.

Theories of unemployment based on search and matching frictions (Mortensen and Pissarides (1999) and Pissarides (2000)) rely on idiosyncratic shocks to drive job destruction and match dissolution. A greater intensity of idiosyncratic shocks in these models produces higher match dissolution rates and increased flows of workers into the unemployment pool. The measures of employer volatility and dispersion that we consider provide empirical indicators for the intensity of idiosyncratic shocks. Evidence regarding trends in these indicators can serve as useful inputs into theoretical explanations for longer term movements in the rates of unemployment and match dissolution. These indicators also provide grist for empirical studies of how long term changes in idiosyncratic shock intensity affect unemployment.

Another class of theories stresses the impact of risk-sharing opportunities on the willingness to undertake risky investments. Obstfeld (1994), for example, shows that better diversification opportunities induce a portfolio shift by risk-averse investors toward riskier projects with higher expected returns. Greater portfolio diversification also weakens one motive for organizing production activity around large, internally diversified firms. On both counts, improved opportunities for diversification lead to more volatility and dispersion in producer outcomes. Empirical indicators of increased financial diversification include the rise of mutual funds and institutional investors, lower trading costs for financial securities, higher stock market participation rates by households, and greater cross-border equity holdings. Motivated in part by these developments, Thesmar and Thoenig (2004) build a model whereby a bigger pool of portfolio investors encourages listed firms to adopt riskier business strategies with greater expected profits. More aggressive risk-taking by listed firms also leads unlisted firms to adopt riskier strategies in their model, raising firm level volatility throughout the economy.[6] In the model of Acemoglu (2005), risk-taking by firms increases with aggregate capital accumulation, technical progress and financial development, so that firm volatility naturally rises with economic development. Acemoglu stresses that his model can deliver rising firm volatility accompanied by falling aggregate volatility.

In contrast, Koren and Tenreyro (2006) highlight a mechanism that generates declines in both aggregate and firm volatility as an economy develops. In their model, input variety rises naturally with economic development. As input variety expands, shocks to the productivity of specific varieties lead to less output volatility, provided that the correlation of variety-specific shocks is imperfect and not rising in the number of varieties. Koren and Tenreyro argue that this economic mechanism linking development to input variety helps to explain the negative relationship between GDP per capita and the volatility of GDP growth rates across countries and over time within countries. Whether economic development ultimately dampens firm volatility through the impact of greater input variety or amplifies it as a result of better opportunities for financial diversification is obviously an empirical question.

Another line of research stresses the role of competition in goods markets. Philippon (2003) considers a model with nominal rigidities that links goods-market competition to firm and aggregate volatility. In his model, greater competition in the form of a bigger substitution elasticity among consumption goods magnifies the effects of idiosyncratic shocks on profitability. As a result, greater competition leads to more firm volatility in sales growth rates and a higher frequency of price adjustments. In turn, more frequent price adjustments dampen the response to aggregate demand disturbances in a calibrated version of the model. Thus, insofar as aggregate demand shocks drive aggregate fluctuations, Philippon's model produces divergent trends in aggregate and firm volatility. Comin and Mulani (2005) argue that increased R&D-based competition leads to more firm volatility but weaker comovements and, hence, lower aggregate volatility. As Acemoglu (2005) points out, however, R&D investments can act to increase or decrease competitive intensity, and the link to aggregate volatility is also tenuous. Comin and Philippon (2005) point to deregulation as a source of greater goods-market competition and rising firm level volatility. While deregulation is likely to increase firm volatility in the short term, its longer term impact is less clear. For example, when regulatory restrictions hamper horizontal consolidation, deregulation can lead to an industry structure with fewer, larger firms. Horizontal consolidation is, in turn, a force for less firm level volatility. The removal of regulatory restrictions on branching and interstate banking accelerated this type of evolutionary pattern in the U.S. banking sector (Jayaratne and Strahan 1998).

Although much recent work focuses on the potential for better risk-sharing opportunities or greater goods-market competition to produce opposite trends in aggregate and firm level volatility, there is a simple mechanical reason to anticipate that micro and macro volatility will trend in the same direction. To see the argument, write the firm level growth rate as a linear function of K aggregate shocks that (potentially) affect all firms and an idiosyncratic shock, ε_i, that affects only firm i:

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

The aggregate growth rate is $\Sigma_i \alpha_{it} \gamma_{it}$, where α_i is firm i's share of aggregate activity. Assuming mutually uncorrelated shocks, equation (1) implies the following expressions for firm level and aggregate volatility:

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

$$\text{Aggregate Volatility} = \sum_{i}^{n} \alpha_{it}^2 \sigma_{it}^2 + \sum_{i}^{n} \alpha_{it}^2 \left[\sum_{k=1}^{K} \beta_{ik}^2 \sigma_{kt}^2 \right] \tag{3}$$

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

In light of the positive comovements that typify aggregate fluctuations, we assume that the weighted cross-product of the β coefficients is positive for each k.

Inspecting (2) and (3), we see that firm and aggregate volatility respond in the same direction to a change in any one of the shock variances, provided that the firm shares α_i and the shock response coefficients β_{ik} are reasonably stable. In particular, a decline in the variability of aggregate shocks leads to a decline in both aggregate and firm volatility. Hence, insofar as the well-established secular decline in aggregate volatility reflects a decline in the size or frequency of aggregate shocks, we anticipate a decline in average firm volatility as well. Another argument stresses the importance of idiosyncratic shocks to large firms. Especially if σ_i is independent of size (α_i) at the upper end of the firm size distribution, as in Gabaix's (2005) granular theory of aggregate fluctuations, trend changes in the idiosyncratic shock variance for, say, the 100 largest firms can be a powerful force that drives micro and macro volatility in the same direction. Of course, (2) and (3) do not require that aggregate and firm volatility trend in the same direction. A mix of positive and negative changes in the shock variances could drive micro and macro volatility measures in opposite directions, as could certain changes in the pattern of shock-response coefficients or the firm size distribution. Still, big trends in the opposite direction for micro and macro volatility strike us as an unlikely outcome.

Evolutions in market structure can also drive the trend in firm volatility, particularly in sectors that undergo sweeping transformations. Consider Retail Trade. The expansion of Wal-Mart, Target, Staples, Best Buy, Home Depot, Borders, and other national chains has propelled the entry of large retail outlets and displaced thousands of independent and smaller retail establishments and firms. Jarmin, Klimek, and Miranda (2005) report that the share of U.S. retail activity accounted for by single-establishment firms fell from 60 percent in 1967 to 39 percent in 1997. In its initial phase, this transformation involved high entry and exit rates, but over time the Retail Trade size distribution shifted towards larger establishments and much larger firms. Empirical studies routinely find a strong negative relationship between business size and volatility. Hence, we anticipate that the transformation of the retail sector led to a secular decline in the volatility and dispersion of growth rates among retail businesses.

One other key issue involves the impact of developments that expand business access to equity markets. Financial developments of this sort can profoundly alter the mix of publicly traded firms and drive volatility trends among all listed firms that are unrepresentative of trends for seasoned listings and the economy as a whole. Some previous studies point strongly in that direction. For example, Fama and French (2004) report that the number of new lists (mostly IPOs) on major U.S. stock markets jumped from 156 per year in 1973–1979 to 549 per year in 1980–2001. Remarkably, about 10 percent of listed firms are new each year from 1980 to 2001. Fama and French also provide compelling evidence that new lists are much riskier than seasoned firms and increasingly so from 1980 to 2001. They conclude that the upsurge of new listings explains much of the trend increase in idiosyncratic stock return volatility documented by Campbell et al. (2001). They also suggest that there was a decline in the cost of equity that allowed weaker firms and those with more distant payoffs to issue public equity. Fink et al. (2005) provide additional evidence in support of these conclusions. Drawing on data from Jovanovic and Rousseau (2001), they report that firm age at IPO date (measured from its founding date or date of incorporation) fell dramatically from nearly 40 years old in the early 1960s to less than five years old by the late 1990s. They find that the positive trend in idiosyncratic risk is fully explained by the proportion of young firms in the market. After controlling for age and other measures of firm maturity (book-to-market, size, profitability), they find a negative trend in idiosyncratic risk. These studies imply that the selection process governing entry into the set of publicly traded firms shifted dramatically after 1979, and that the shift continued to intensify through the late 1990s.

3 Data and Measurement

3.1 *Source Data: The LBD and COMPUSTAT*

The Longitudinal Business Database (LBD) is constructed from the Census Bureau's Business Register of U.S. businesses with paid employees and enhanced with survey data collections. The LBD covers all sectors of the economy and all geographic areas and currently runs from 1976 to 2001. In recent years, it contains over six million establishment records and almost five million firm records per year. Basic data items include employment, payroll, 4-digit SIC, employer identification numbers, business name, and information about location.[7] Identifiers in the LBD files enable us to compute growth rate measures for establishments and firms.[8] Firms in the LBD are defined based on operational control, and all establishments that are majority owned by the parent firm are included as part of the parent's activity measures. We restrict attention in this study to nonfarm businesses in the private sector.

We also exploit COMPUSTAT data from 1950 to 2004.[9] A unit of observation in COMPUSTAT is a publicly traded security identified by a CUSIP. We exclude certain CUSIPs because they reflect duplicate records for a particular firm, multiple security issues for the same firm, or because they do not correspond to firms in the usual sense. Duplicate entries for the same firm (reflecting more than one 10-K filing in the same year) are few in number but can be quite large (more than 500,000 workers). We also exclude CUSIPs for American Depository Receipts (ADRs)—securities created by U.S. banks to permit U.S.-based trading of stocks listed on foreign exchanges. All together, we exclude approximately 1,100 CUSIPs because of duplicates and ADRs. The presence of duplicates, ADRs and other features of COMPUSTAT imply the need for caution in measuring firm outcomes and in linking COMPUSTAT records to the LBD.

We use COMPUSTAT to supplement the LBD with information on whether firms are publicly traded. For this purpose, we created a bridge file that links LBD and COMPUSTAT records based on business taxpayer identification numbers (EINs) and business name and address.[10] Missing data on equity prices, sales and employment data for some COMPUSTAT records do not cause problems for our LBD-based analysis, because we rely on LBD employment data whether or not the COMPUSTAT data are missing. Our matching procedures also work when there are holes in the COMPUSTAT data. In particular, we classify a firm in the LBD as publicly traded in a given year if it matches to a COMPUSTAT CUSIP by EIN or name and address, and if the CUSIP has non-missing equity price data in the same year or in years that bracket the given year.

Table 2.1 presents LBD and COMPUSTAT summary statistics for firm counts, employment and firm size in selected years. As of 2000, the LBD has almost five million firms with positive employment in the nonfarm private sector, of which we identify more than 7,000 as publicly traded. Average LBD firm size in 2000 is about 18 employees, which is tiny compared to the average of 4,000 employees for publicly traded firms. Publicly traded firms account for a trivial fraction of all firms and less than one-third of nonfarm business employment during the period covered by the LBD. The highly skewed nature of the firm size distribution is also apparent in the enormous difference between average firm size and the employment-weighted mean firm size (the coworker mean). For example, the upper panel of table 2.1 reports a coworker mean of 92,604 employees at publicly traded firms in the LBD in 2000, roughly 23 times larger than the simple mean of firm size. The highly skewed nature of the firm size distribution implies the potential for equally weighted and size-weighted measures of business volatility and dispersion to behave in dissimilar ways.

Table 2.1
Summary Statistics for COMPUSTAT, LBD, and Matched Data Sets

A. Summary Statistics for LBD Using LBD/COMPUSTAT Bridge

Year		Number of Firms	Total Employment	Average Employment	Coworker Mean
	Privately Held	3,530,307	51,622,693	14.6	2,736
1980	Publicly Traded (Bridge)	4,339	21,045,202	4,850.2	67,983
	Total	3,534,646	72,667,895	20.6	21,632
	Privately Held	4,222,385	68,896,957	16.3	4,235
1990	Publicly Traded (Bridge)	5,739	22,930,762	3,995.6	73,533
	Total	4,228,124	91,827,719	21.7	21,540
	Privately Held	4,744,020	83,845,864	17.7	4,761
2000	Publicly Traded (Bridge)	7,338	29,469,013	4,015.9	92,604
	Total	4,751,358	113,314,877	23.8	27,605

B. Summary Statistics for COMPUSTAT Using LBD/COMPUSTAT Bridge

Year		Number of CUSIPS with Positive Price	Number of CUSIPS with Positive Employment	Total Employment	Average Employment	Coworker Mean
	LBD Match (Bridge)	3,995	4,672	29,729,396	6,363	114,630
1980	Not Matched	835	880	3,841,700	4,366	39,050
	Total	4,830	5,552	33,571,096	6,047	105,981
	LBD Match (Bridge)	5,986	5,716	31,755,052	5,555	110,374
1990	Not Matched	847	523	2,793,759	5,342	72,865
	Total	6,833	6,239	34,548,811	5,538	107,341
	LBD Match (Bridge)	8,394	7,168	40,672,986	5,674	137,678
2000	Not Matched	2,063	1,306	4,090,947	3,132	53,033
	Total	10,457	8,474	44,763,932	5,283	137,570

Notes: In panel A, an LBD firm is identified as publicly traded if it appears in the LBD/COMPUSTAT Bridge and its COMPUSTAT CUSIP has a positive security price in the indicated year or in years that bracket the indicated year. In panel B, a COMPUSTAT firm is identified as an LBD match if the CUSIP appears in the LBD/COMPUSTAT Bridge. In panel B, we do not require the LBD match to have positive payroll in the current year. In both panels, average employment is the simple mean over firms, and the coworker mean is the employment-weighted mean firm size.

Comparisons between the upper and lower panels of table 2.1 require some care, because the LBD and COMPUSTAT differ in how they define a firm and in how key variables are measured. LBD employment reflects the count of workers on the payroll during the pay period covering the 12th of March. The employment concept is all employees subject to U.S. payroll taxes. COMPUSTAT employment is the number of company workers reported to shareholders. It may be an average number of employees during the year or a year-end figure. More important, it includes all employees of consolidated subsidiaries, domestic and foreign. For this reason, discrepancies between the LBD and COMPUSTAT are likely to be greater for large multinationals and for foreign firms with U.S. operations (and listings on U.S. stock exchanges). Since the source data from annual reports can be incomplete, some COMPUSTAT firms have missing employment even when the firm has positive sales and a positive market value.

With these cautions in mind, consider the lower panel of table 2.1 and its relationship to the upper panel. The lower panel provides information about the match rate in the LBD/COMPUSTAT Bridge. In 1990, for example, there are 6,239 CUSIPs with positive COMPUSTAT employment. We match 5,716 of these CUSIPs to firms in the LBD, which amounts to 92 percent of COMPUSTAT firms with positive employment and 92 percent of COMPUSTAT employment.[11] It is instructive to compare total employment, average firm size and the coworker mean between the upper and lower panels of table 2.1 for the bridge cases. COMPUSTAT figures for these quantities exceed the corresponding LBD statistics by a very wide margin in all years. For example, among matched publicly traded firms in the Bridge file, the LBD employment figure (Panel A) is only 70.8 percent of COMPUSTAT employment (Panel B) in 1980, 72.2 percent in 1990, and 72.5 percent in 2000. These large discrepancies for matched cases reflect significant differences in the LBD and COMPUSTAT employment concepts, e.g., domestic versus global operations. See the Data Appendix for additional comparisons between the two data sources.

We can use the information reported in table 2.1 to construct an estimate for the percentage of nonfarm business employment in publicly traded firms. First, adjust the COMPUSTAT employment totals for "Not Matched" cases in Panel B by multiplying by the ratio of LBD-to-COMPUSTAT employment for matched cases. Second, add the adjusted COMPUSTAT employment figure for "Not Matched" cases to LBD employment for "Publicly Traded (Bridge)" cases in Panel A, and then divide the sum by LBD nonfarm business employment. The resulting estimates imply that publicly traded firms account for 32.7 percent of nonfarm business employment in 1980, 27.2 percent in 1990, and 28.6 percent in 2000.

To sum up, the LBD provides data from 1976 to 2001 on the universe of firms and establishments with at least one employee in the U.S. private sector. We identify publicly traded firms in the LBD using our COMPUSTAT/LBD Bridge. The empirical analysis below focuses on the LBD, but we also carry out several exercises using COMPUSTAT data.

3.2 *Measuring Firm Growth, Volatility and Cross Sectional Dispersion*

We focus on employment as our activity measure because of its ready availability in the LBD and COMPUSTAT. Recall from figure 2.1 that volatility trends for employment and sales growth rates are similar in COMPUSTAT data. We use a growth rate measure that accommodates entry and exit. In particular, our time-t growth rate measure for firm or establishment i is

$$\gamma_{it} = \frac{x_{it} - x_{it-1}}{(x_{it} + x_{it-1})/2}. \tag{4}$$

This growth rate measure has become standard in work on labor market flows, because it offers significant advantages relative to log changes and growth rates calculated on initial employment. In particular, it yields measures that are symmetric about zero and bounded, affording an integrated treatment of births, deaths, and continuers. It also lends itself to consistent aggregation, and it is identical to log changes up to a second-order Taylor Series expansion. See Tornqvist, Vartia, and Vartia (1985) and the appendix to Davis, Haltiwanger, and Schuh (1996) for additional discussion.

To characterize the variability of business outcomes, we consider several measures of cross sectional *dispersion* in business growth rates and *volatility* in business growth rates. Our basic dispersion measure is the cross sectional standard deviation of the annual growth rates in (4), computed in an equal-weighted or size-weighted manner. Our basic volatility measure follows recent work by Comin and Mulani (2005,

2006) and Comin and Philippon (2005), among others. They measure volatility for firm i at t by

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

where $\bar{\gamma}_{it}$ is the simple mean growth rate for i from $t - 4$ to $t + 5$. This measure requires ten consecutive observations on the firm's growth rates; hence, short-lived firms and entry and exit are not captured.[12]

Limiting the analysis to firms and establishments with ten consecutive years of positive activity is quite restrictive. Hence, we also consider a modified volatility measure that incorporates entry and exit and short-lived business units. The modified measure differs from the basic measure in two main respects. First, we weight the squared deviation at t for firm i in proportion to its size at t relative to its average size in the ten-year window from $t - 4$ to $t + 5$. Second, we apply a standard degrees-of-freedom correction to avoid the small-sample bias that otherwise arises for second moment estimates.[13] We ignored this issue in the basic volatility measure, following standard practice, because the correction is the same for all firms and would simply scale up the volatility magnitude by (10/9). However, the correction matters when some firms have much shorter intervals of positive activity than others. The degrees-of-freedom correction also enables us to obtain unbiased estimates for average volatility near the LBD and COMPUSTAT sample end points, which truncate the available window for estimating firm level volatility.

Here are the details for constructing our modified volatility measure. Let $z_{it} = .5(x_{it} + x_{it-1})$ denote the size of firm i at time t, and let P_{it} denote the number of years from $t - 4$ to $t + 5$ for which $z_{it} > 0$. Define the scaling quantity,

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

and the rescaled weights, $\tilde{z}_{it} = K_{it} z_{it}$. By construction,

$$\sum_{\tau=-4}^{5} \tilde{z}_{it} = P_{it}.$$

The modified firm volatility measure with degrees-of-freedom correction is given by

$$\tilde{\sigma}_{it} = \left[\sum_{\tau=-4}^{5} \left(\frac{\tilde{z}_{i,t+\tau}}{P_{it} - 1} \right) (\gamma_{i,t+\tau} - \overline{\gamma}_{it}^{w})^2 \right]^{1/2}, \tag{6}$$

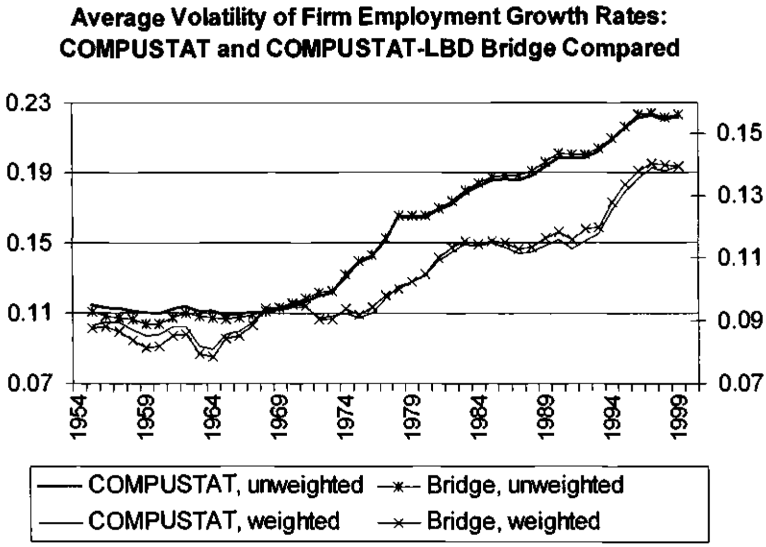
where $\overline{\gamma}^{w}_{it}$ is firm i's size-weighted mean growth rate from $t - 4$ to $t + 5$, using the z_{it} as weights. We construct this measure for all businesses in year t with a positive value for z_{it}. In other words, we compute (6) on the same set of firms as the contemporaneous dispersion measure.

The average magnitude of firm volatility at a point in time can be calculated using equal weights or weights proportional to business size. We prefer size-weighted volatility (and dispersion) measures for most purposes, but we also report some equal-weighted measures for comparison to previous work. In the size-weighted measures, the weight for business i at t is proportional to z_{it}.

Summing up, our dispersion measures reflect year-to-year, between-firm variation in growth rates. Our volatility measures reflect year-to-year, within-firm variation in growth rates. Some volatility measures restrict analysis to long-lived firms, but we also consider modified volatility measures defined over the same firms as contemporaneous dispersion measures. Volatility and dispersion measures have different properties, and they highlight different aspects of business growth rate behavior. Still, they are closely related concepts. For example, if business growth rates are drawn from stochastic processes with contemporaneously correlated movements in second moments, then the cross-sectional dispersion in business growth rates and the average volatility of business growth rates are likely to move together over longer periods of time.[14]

3.3 Firm Volatility—Robustness to the Bridge Cases

To assess whether our results are sensitive to the use of publicly traded firms in the LBD/COMPUSTAT Bridge, we compare firm volatility for the full COMPUSTAT to firm volatility for matched cases. We consider all CUSIPs that match to the LBD in any year during the LBD overlap from 1976 to 2001. Figure 2.3 displays the comparison. It shows that restricting attention to those publicly traded firms that we identify in the LBD/COMPUSTAT Bridge has no material effect on the volatility results. This result gives us confidence that our LBD-based comparisons below of publicly traded and privately held firms are not distorted by inadequacies in our matching algorithm.



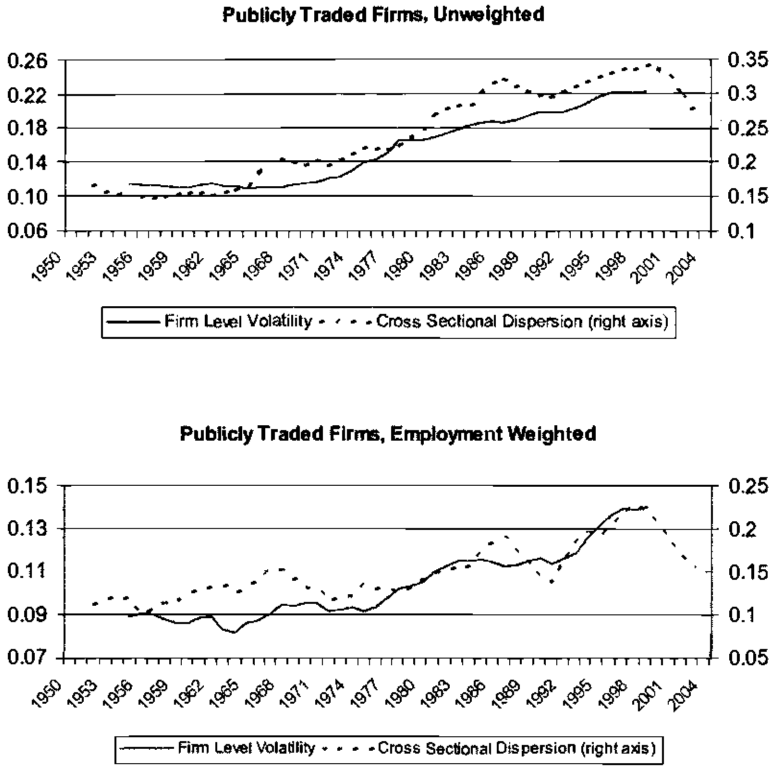
Source: Own calculations on COMPUSTAT data and COMPUSTAT-LBD Bridge file.
Notes: Calculations exclude COMPUSAT entry and exit. Firm volatility calculated according to equation (5).

Figure 2.3
Full COMPUSTAT Compared to COMPUSTAT-LBD Bridge File

4 Business Volatility and Dispersion Trends

4.1 Results Using COMPUSTAT Data on Publicly Traded Firms

We now compare the volatility and dispersion in business growth rates using COMPUSTAT data. At this point, we do not restrict attention to firms in the Bridge file.[15] Figure 2.4 shows the now-familiar pattern of rising firm volatility overlaid against a similar trend for the cross sectional dispersion of firm growth rates. To ensure an apples-to-apples comparison, we calculate dispersion using only those firm-year observations for which we calculate firm volatility. While the volatility and dispersion measures capture different aspects of business dynamics, figure 2.4 shows that they closely track each other over the longer term. Similar results obtain for sales-based volatility and dispersion measures and for dispersion measures calculated on all firm-year observations. However, dispersion is uniformly larger than average firm volatility. That is, between-firm variation in annual growth



Source: Own calculations on COMPUSTAT data.

Notes: Calculations exclude COMPUSTAT entry and exit. Firm volatility calculated according to equation (5).

Figure 2.4
Firm Volatility and Dispersion of Employment Growth Rates Compared, COMPUSTAT Data

rates exceeds the average within-firm variation. The gap between the dispersion and volatility measures shown in figure 2.4 expanded over time from about 4 percentage points in 1955 to 7 percentage points in 1999.

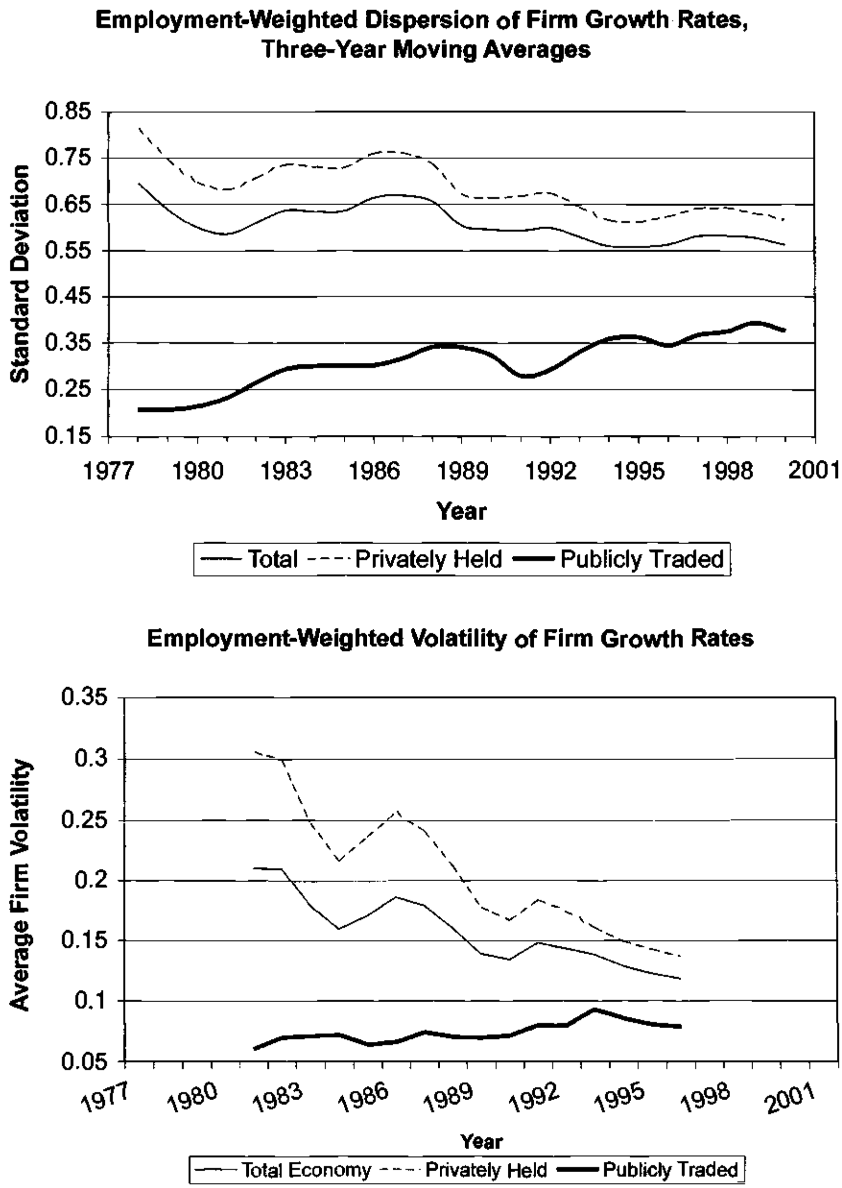
Figure 2.4 also shows that weighted measures are considerably smaller than the corresponding unweighted measures at all times. This pattern reflects the greater stability of growth rates at larger firms. The weighted measures also show a smaller and less steady upward trend than the unweighted measures, as we saw in figure 2.1. The rest of the paper reports weighted measures of dispersion and volatility, because we think they are more relevant for aggregate behavior. Moreover, on an unweighted basis, publicly traded firms have negligible effects on dispersion and volatility measures for the private sector as a whole, because they are so few in number.

4.2 Results Using Firm Level Data in the Longitudinal Business Database

A concern with COMPUSTAT-based results is whether they generalize to the entire economy. Figure 2.5 exploits LBD data to address this concern.[16] The figure shows large declines in the volatility and dispersion of firm growth rates for the whole nonfarm private sector and even larger declines among privately held firms. The dispersion in growth rates falls by about 13 percentage points from 1978 to 2000 in the private sector and by about 20 percentage points among privately held firms.[17] The average magnitude of firm volatility falls by about 10 percentage points from 1981 to 1996 in the private sector and by about 17 percentage points among privately held firms. The volatility decline in the private sector over this period is more than 40 percent of its 1981 value, a striking contrast to the rise in volatility among publicly traded firms over the same period.

The LBD-based results also show that privately held firms are much more volatile than publicly traded firms, and their growth rates show much greater dispersion. This pattern is not particularly surprising, because a bigger share of activity in the publicly traded sector is accounted for by older and larger firms that tend to be relatively stable. As figure 2.5 shows, however, publicly traded and privately held firms are converging in terms of the volatility and dispersion of their growth rates. We return to this matter shortly.

The finding that firm volatility in the private sector falls over time is consistent with previous findings in the job flows literature (figure 2.2). It is also consistent with previous research using the LBD. One of the earliest findings from the LBD is a steady decline in establishment entry rates (Foster (2003) and Jarmin, Klimek, and Miranda (2003)). Recent work also finds declining entry and exit rates in local retail markets for establishments and firms (Jarmin, Klimek, and Miranda 2005). Jarmin et al. stress the changing structure of retail trade as one factor underlying the decline in entry and exit. They document the increasing share of activity accounted for by large, national retail chains with many establishments.[18] This change in industry structure has a power-



Source: Own calculations on LBD data.

Notes: Calculations in the top panel include entry and exit. Firm volatility in the bottom panel is calculated according to equation (5) and, hence, excludes short-lived firms.

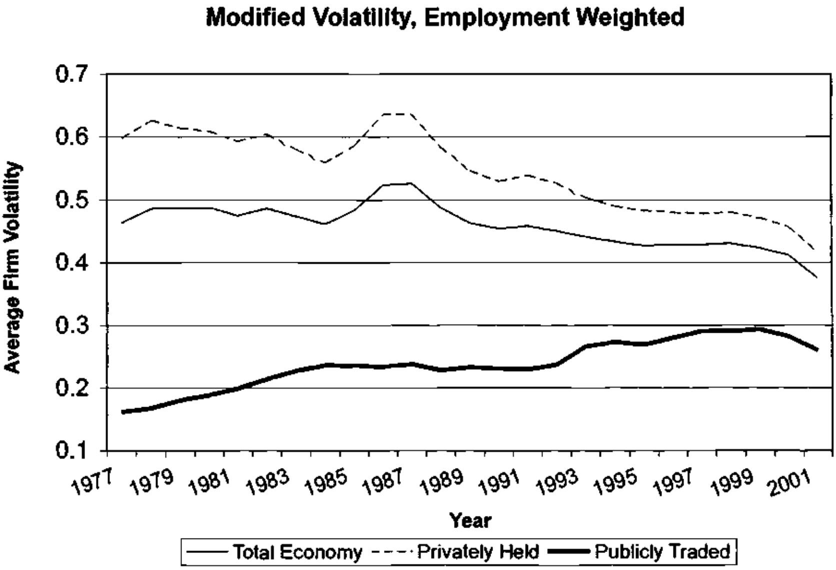
Figure 2.5

Dispersion and Volatility of Employment Growth Rates by Ownership Status, LBD Data ful effect, because entry and exit rates are substantially higher for small, single-unit firms than for large national chains. We return to the role of industry structure and business turnover in section 5.

All volatility series displayed thus far are based on equation (5) and limited to firms with at least ten consecutive observations. This selection criterion is especially restrictive for privately held firms, most of which do not survive ten years. By and large, privately held firms are relatively volatile, and so are short-lived firms. If the objective is to examine the overall magnitude of firm volatility, then it is desirable to use datasets and statistics that capture the most volatile units in the economy. To do so, we now use LBD data to calculate modified volatility measures based on equation (6). Figure 2.6 shows the results for the employment-weighted modified volatility measure. As before, volatility is higher and falling for privately held business, lower and rising for publicly traded firms. Modified volatility for privately held firms falls from 0.60 in 1977 to 0.42 in 2001, with the entire fall occurring after 1987. Modified volatility for publicly traded firms rises from 0.16 in 1977 to 0.29 in 1999.

4.3 *Volatility Convergence across Major Industry Groups*

The most striking features of figures 2.5 and 2.6 are the opposite trends for publicly traded and privately held firms and the dramatic convergence in their volatility levels. Table 2.2 shows that these two features hold in every major industry group. Among publicly traded firms, modified volatility rises for all industry groups, though by widely varying amounts. The biggest volatility gains among publicly traded firms occur in Transportation and Public Utilities, Wholesale, FIRE, and Services. Among privately held firms, the modified volatility measure declines by 23 percent for FIRE and by 30 percent or more for all other industry groups. Overall volatility in the nonfarm business sector declines for every industry group, with drops of more than 30 percent in Construction, Wholesale, Retail, and Services. The volatility convergence phenomenon is also present in every industry group. Between 1978 and 2001, the ratio of volatility among privately held firms to volatility among publicly traded firms fell from 3.2 to 1.7 in Manufacturing, from 6.3 to 1.8 in Transportation and Public Utilities, from 4.2 to 2.2 in Retail, from 3.3 to 1.3 in FIRE, and from 2.3 to 1.1 in Services.



Source: Own calculations on LBD data.

Notes: Calculations include entry and exit and short-lived firms. Firm volatility calculated according to equation (6).

Figure 2.6
Modified Measure of Volatility in Firm Growth Rates, 1977–2001, LBD Data

5 Exploring and Refining the Main Results

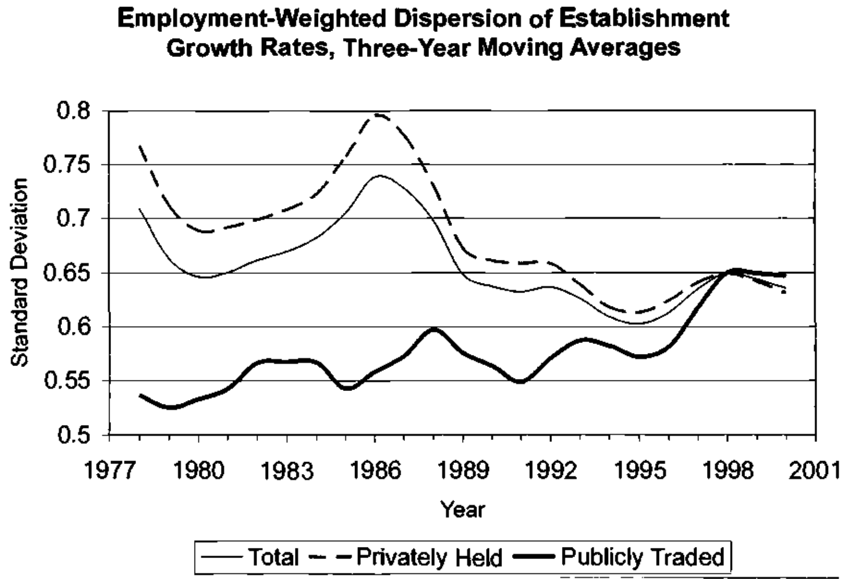
5.1 Establishment-Based Measures

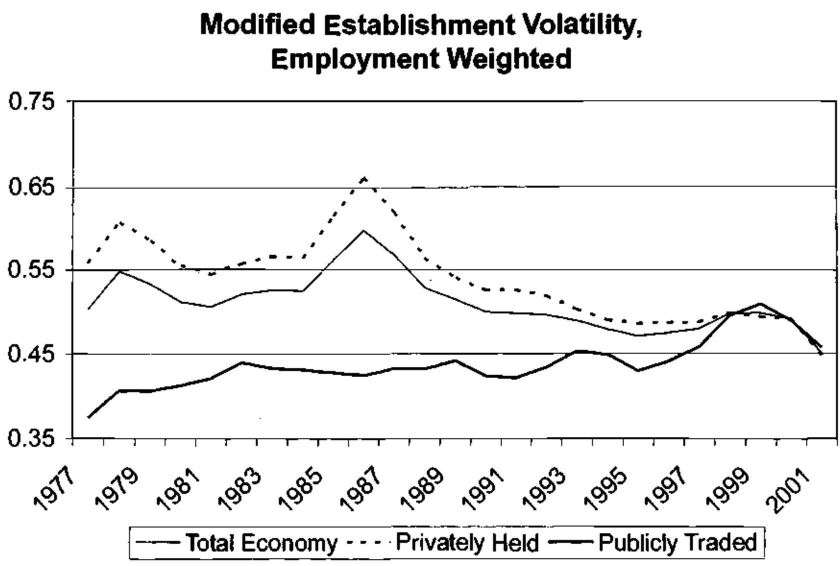
Trends in the volatility and dispersion of establishment growth rates can differ from trends for firm growth rates. In particular, a shift over time towards multi-unit firms yields declines in the volatility and dispersion of firm growth rates through a simple statistical aggregation effect. If two establishments with imperfectly correlated growth rates combine into a single firm, for example, then the volatility of the firm's growth rates is lower than the average volatility for the two establishments. As mentioned earlier, the Retail Trade sector has undergone a pronounced shift away from single-unit firms to national chains. Motivated by these observations, figure 2.7 shows the employment-weighted dispersion and volatility of establishment growth rates, calculated from

Table 2.2
Firm Volatility Trends by Major Industry Group and Ownership Status

	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	Percent 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

Notes: Modified firm volatility measures calculated according to equation (6) with LBD data. Average volatility across firms computed on an employment-weighted basis.





Source: Own calculations on LBD data.

Notes: Calculations include entry and exit and short-lived establishments. Modified establishment volatility calculated according to equation (6).

Figure 2.7
Dispersion and Volatility of Establishment Growth Rates, LBD Data

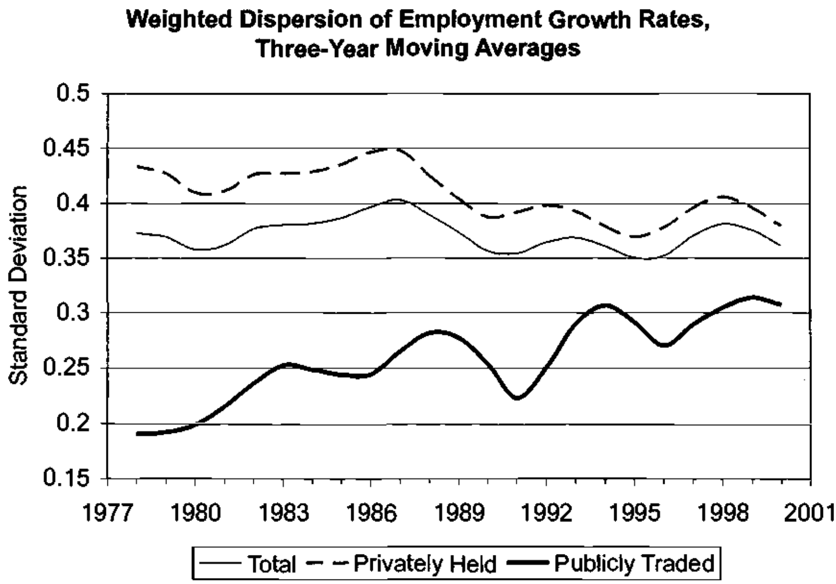
LBD data. Publicly traded establishments are those owned by publicly traded firms. In line with the statistical aggregation effect, the levels of volatility and dispersion are substantially higher for publicly traded establishments than for publicly traded firms.

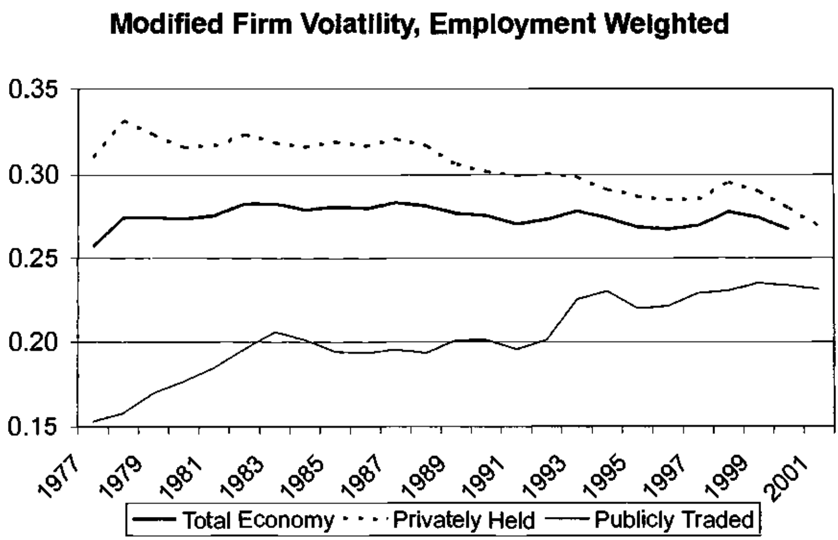
As seen in figure 2.7, the basic patterns for establishment-based measures are the same as for firm-based measures. Dispersion and volatility fall for the privately held, and they rise for the publicly traded. As before, the overall trend for the nonfarm business sector is dominated by privately held businesses. Some differences between the firm-based and establishment-based results are also apparent. Rather remarkably, there is full volatility convergence between publicly traded and privately held establishments by the end of the LBD sample period. In sum, figure 2.7 shows that our main results are not sensitive to the distinction between firms and establishments.

5.2 *The Role of Entry and Exit*

Figure 2.8 shows the dispersion and volatility of employment growth rates for continuing firms only. We calculate these measures on an employment-weighted basis from LBD data, after excluding entry-year and exit-year observations at the firm level. The exclusion of entry and exit mutes the downward trends for privately held firms and for the nonfarm sector as a whole. Indeed, the modified volatility measure for the nonfarm business sector is essentially flat from 1977 to 2001 when we restrict attention to continuers. This sample restriction also mutes the rise in volatility and dispersion for publicly traded firms. Not surprisingly, the levels of volatility and dispersion are also much lower when we exclude entry and exit. A comparison of figures 2.5 and 2.8 reveals, for example, that the exclusion of entry and exit lowers the overall dispersion of firm growth rates by about one third.

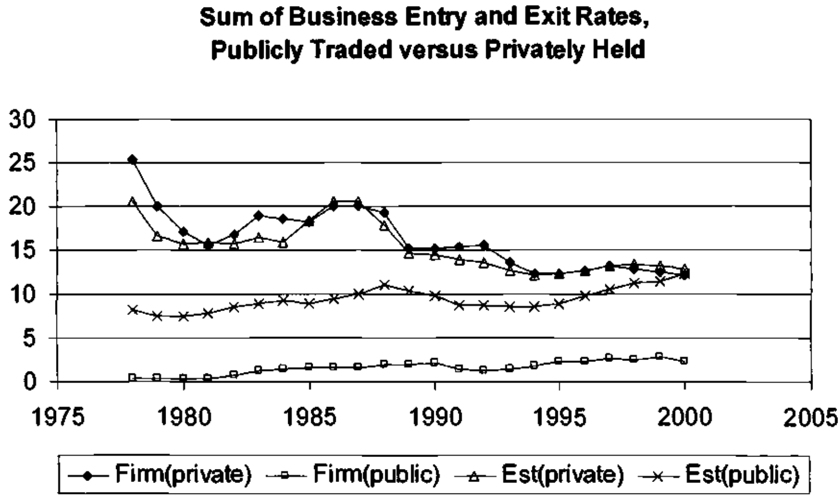
Figure 2.9 provides direct evidence on the magnitude of entry and exit by ownership status for firms and establishments. The figure shows three-year moving averages of the employment-weighted sum of entry and exit, expressed as a percentage of employment. As seen in the figure, the volatility convergence phenomenon also holds for entry and exit rates, whether calculated for establishments or firms. Among privately held businesses, the sum of establishment entry and exit rates declines from 20.6 to 12.9 percent of employment over the period covered by the LBD. It rises from 8.1 to 12.3 percent of





Source: Own calculations on LBD data.
Note: Calculations exclude entry and exit.

Figure 2.8
Dispersion and Volatility of Firm Growth Rates, Continuers Only, LBD Data



Source: Own calculations on LBD data.
Note: The employment-weighted sum of entry and exit rates at t is expressed as a percentage of the simple average of employment in $t - 1$ and t.

Figure 2.9
Employment-Weighted Sum of Entry and Exit Rates for Establishments and Firms by Ownership Status, Three-Year Moving Averages

employment for publicly traded. Thus, there is essentially full volatility convergence by 2001 for establishment-based measures of business turnover.

On average, each publicly traded firm operates about 90 establishments, which implies considerable scope for statistical aggregation. This effect shows up in figure 2.9 as a large gap between firm-based and establishment-based turnover among publicly traded businesses. In contrast, there are only 1.16 establishments per privately held firm, which implies much less scope for statistical aggregation. Indeed, the sum of entry and exit rates for privately held firms exceeds the corresponding establishment-based measure in the early years of the LBD. This feature of figure 2.9 indicates that a portion of the firm entry and exit events identified in the LBD reflects ownership changes for continuing businesses, rather than complete firm shutdowns or de novo entry.[19] Since the gap between firm-based and establishment-based turnover narrows rapidly in the early years of the LBD, figure 2.9 also suggests that we overstate the decline in firm-based measures of dispersion and volatility in the first few years.[20] Despite this concern, several observations give confidence that our main findings about volatility and dispersion trends and volatility convergence are not driven by ownership changes. First, the firm-establishment turnover gap is close to zero after 1984 (figure 2.9). Second, the basic trends and volatility convergence results hold up strongly when we consider establishment-based measures (figure 2.7). Third, our main results also hold when we restrict attention to continuing firms, which exclude improperly broken longitudinal links by construction (figure 2.8).[21]

5.3 *The Role of Size, Age, and Industry Composition*

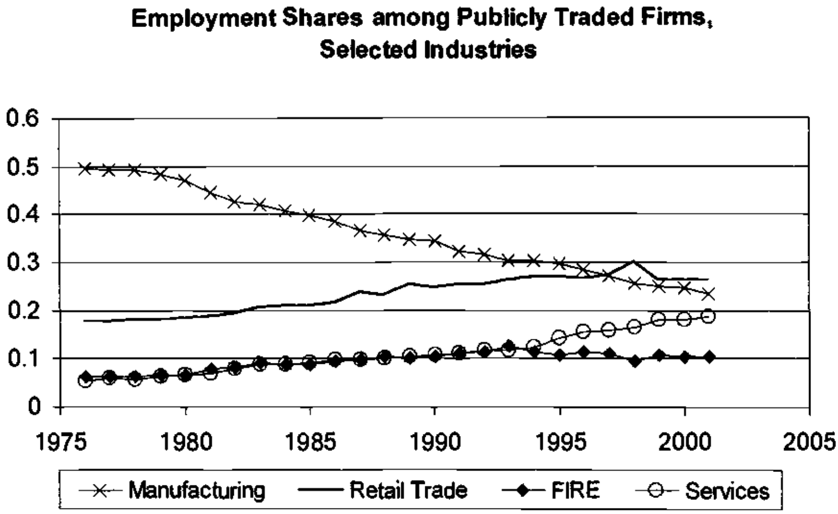
We now investigate whether shifts in the size, age, and industry composition of employment can account for the trends in firm volatility and dispersion. Shifts in the employment distribution along these dimensions have potentially large effects, because volatility and dispersion magnitudes vary by industry and especially by business size and age.[22] To investigate this issue, table 2.3 reports modified volatility measures in 1982 and 2001 alongside the volatility values implied by fixing the industry, age, and/or size distribution of employment at 1982 shares while allowing category-specific volatilities to vary over time as in the data. We employ a cell-based shift-share methodology, where we compute the modified volatility measure for 448 size, age, and industry cells per year. We use 1982 employment shares, because it is the earliest year for which we can identify seven distinct age categories in the LBD data—entrants, 1, 2, 3, 4, 5, and 6+ years of age, where firm age is identified as the age of the firm's oldest establishment. In addition to seven age categories, we consider eight size categories and the eight industry groups listed in table 2.2.

Table 2.3 contains several noteworthy findings. Turning first to publicly traded firms, modified volatility rises by 21 percent from 0.21 in 1982 to 0.26 in 2001. The volatility rise among publicly traded firms is essentially unchanged when we control for shifts in the size and age distribution of employment. In contrast, when we fix the industry employment distribution at 1982 shares, the volatility rise among publicly traded firms is cut by half. To shed additional light on this result, figure 2.10 shows the evolution of selected industry shares among publicly traded firms over the period covered by the LBD. The manufacturing employment share fell from almost 50 percent in the late 1970s to 23 percent in 2001, while the shares accounted for by FIRE, Services, and Retail rose. As reported in table 2.2, volatility among publicly traded

Table 2.3
The Role of Shifts in the Size, Age, and Industry Distribution of Employment

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

Notes: Modified firm volatility measures calculated according to equation (6) with LBD data. Average volatility across firms computed on an employment-weighted basis. The bottom row shows the actual average volatility values in 1982 and 2001 and the percent change. Entries for 2001 in the other rows show the volatility values implied by fixing employment shares at the 1982 distribution over the indicated category variables, while allowing the average volatility within categories to vary as in the data. We use seven firm age categories (entrants, 1, 2, 3, 4, 5, and 6+ years), eight size categories (1–9, 10–19, 20–49, 50–99, 100–249, 500–999, and 1,000+ employees), and the eight industries listed in table 2.2. "Size, Age, and Industry" refers to a fully interacted specification with $7 \times 8 \times 8 = 448$ distinct categories.



Source: Own calculations using LBD data and COMPUSTAT/LBD Bridge.

Figure 2.10
Industry Employment Shares among Publicly Traded Firms, 1976–2001

Manufacturing and Retail firms is about one-fifth lower than overall volatility for publicly traded firms in 2001. In contrast, volatility among publicly traded firms in FIRE and Services is considerably greater. Thus, the large contribution of industry composition changes to the volatility rise among publicly traded firms is basically a story of shifts from Manufacturing to FIRE and Services. The coincident shift to Retail actually muted the rise in volatility among publicly traded firms.

Turning next to privately held firms, table 2.3 reports that volatility fell by 31 percent from 0.60 in 1982 to 0.42 in 2001. In contrast to the story for publicly traded firms, shifts in the industry distribution play essentially no role in the volatility trend for privately held firms. Size effects play a rather modest role. However, when we fix the age distribution of employment at 1982 shares, the volatility drop among privately held firms is cut by 27 percent. This 27 percent figure probably understates the contribution of shifts in the age distribution, because we cannot finely differentiate age among older firms in the early years covered by the LBD.

Table 2.4 provides additional information about the role of shifts in the age distribution among privately held firms. The table confirms

Table 2.4
Employment Shares and Volatility by Firm Age, Privately Held Firms

	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
1982 Age-Specific Volatilities Evaluated at the 2001 Age Distribution of Employment				0.57	
Percentage of 1982–2001 Volatility Decline Accounted for by Shift to Firms 6+ Years Old				19.6	

Additional 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

Source: Own calculations on LBD data.
Notes: Modified firm volatility measures calculated according to equation (6). Average volatility across firms computed on an employment-weighted basis.

that volatility declines steeply with firm age. Note, also, that the share of employment in firms at least six years old increases from 75.6 percent in 1982 to 83.6 percent in 2001, *and* that volatility drops much more sharply in the six+ category than any other age category. Moreover, average volatility by age among privately held firms continues to decline through 25 years of age in 2001, as reported in the lower part of table 2.4. These results are highly suggestive of unmeasured shifts from 1982 to 2001 in the age distribution of employment toward older, less volatile firms within the six+ category. Hence, we conclude that shifts in the age distribution of employment among privately held firms probably account for more than the 27 percent figure suggested by table 2.3.[23]

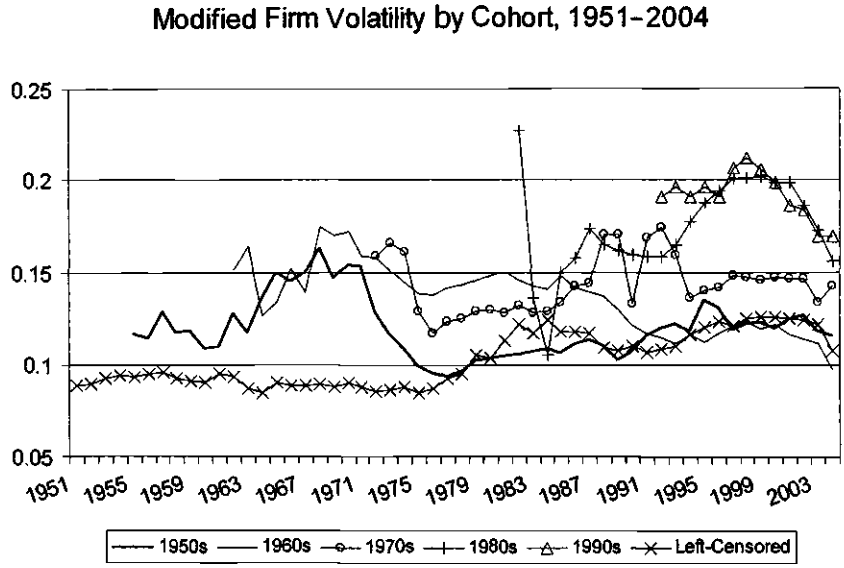
Turning last to the results for all firms, table 2.3 implies that shifts in the age distribution of employment account for 29 percent of the volatility decline. Size effects alone account for 10 percent of the overall volatility decline. In unreported results that use a finer size breakdown, we find that a shift toward larger firms accounts for 25 percent of the volatility decline in Retail Trade.[24] These results are related to the decline in the employment-weighted entry and exit rates among privately held firms, documented in figure 2.9. Since older and larger firms have lower exit rates, a shift of employment toward these firms leads to lower rates of firm turnover. Lastly, table 2.3 implies that shifts in the industry mix of employment actually work against the overall volatility decline among nonfarm businesses.

5.3 *Why the Rise in Volatility among Publicly Traded Firms?*

As discussed in section 2, there was a large upsurge in the number of newly listed firms after 1979. Fama and French (2004), among others, provide evidence that new listings are riskier than seasoned public firms, and that they became increasingly risky relative to seasoned firms after 1979. These pieces of evidence point to a significant change in the economic selection process governing entry into the set of publicly traded firms. They also suggest that much of the volatility and dispersion rise among publicly traded firms reflects a large influx of more volatile firms in later cohorts.

We now investigate this issue, focusing on the modified volatility concept for publicly traded firms. We rely on COMPUSTAT for this purpose, because it spans a much longer period than the LBD. The scope of COMPUSTAT expanded in certain years during our sample period, e.g., NASDAQ listings first became available as part of COMPUSTAT in 1973. Since COMPUSTAT does not accurately identify first listing year for firms that are added to COMPUSTAT because of changes in scope, we drop such firms from the data set for the present analysis.[25] As before, we intentionally exclude entry-year and exit-year observations in the COMPUSTAT data because listing and delisting typically do not reflect the birth or shutdown of the firm.

Figure 2.11 plots modified volatility time series for ten-year entry cohorts, defined by time of first listing. Volatility appears to be somewhat higher for the 1960s and 1970s cohort than earlier cohorts, and it is *much* higher still for the 1980s and 1990s cohorts.[26] To help understand how these cohort effects influence the evolution of overall volatility



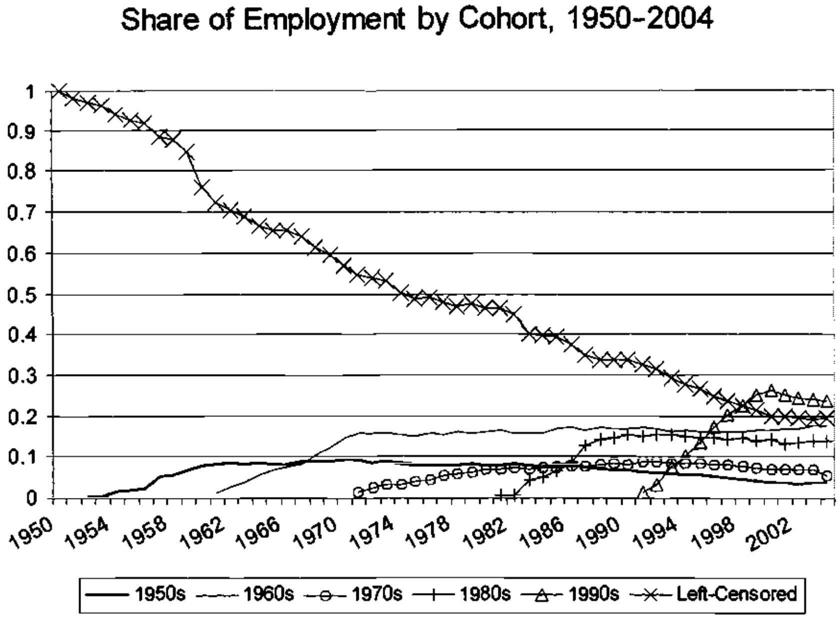
Source: Own calculations on COMPUSTAT data.

Notes: Calculations exclude entry and exit. Firm volatility calculated according to equation (6). Average volatility computed on an employment-weighted basis.

Figure 2.11
Modified Volatility by Cohort among Publicly Traded Firms

among publicly traded firms, figure 2.12 displays cohort employment shares over the period covered by COMPUSTAT. This figure shows that cohort employment shares initially grow quite rapidly, and that this effect is especially strong for the 1990s cohort. By the latter part of the 1990s, firms that first listed in the 1980s or 1990s account for about 40 percent of employment among publicly traded firms. Taken together, figures 2.11 and 2.12 suggest that cohort effects play a powerful role in the volatility rise among publicly traded firms.

Figure 2.13 quantifies the contribution of cohort effects to the evolution of volatility among publicly traded firms. For the sake of comparison, the figure also provides information about the contribution of size, age, and industry effects. To construct figure 2.13, we first fit employment-weighted regressions of firm volatility on year effects and other variables using COMPUSTAT data from 1951 to 2004. Our basic specification regresses firm volatility on year effects only. The fitted year

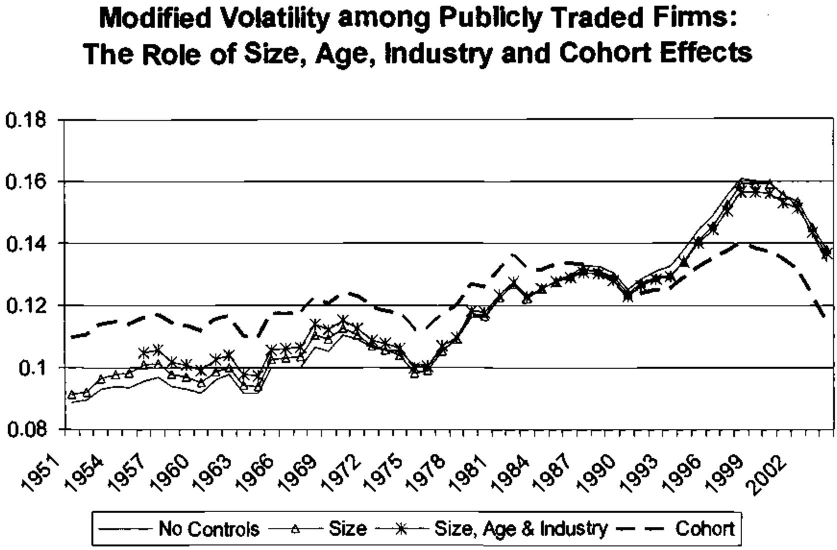


Source: Own calculations on COMPUSTAT data.

Figure 2.12
Employment Shares by Cohort, Publicly Traded Firms

effects in this basic specification yield the "No Controls" series plotted in figure 2.13. Next, we expand the basic specification to include indicators for one-year entry cohorts. The fitted year effects in this expanded specification yield the "Cohort" series plotted in figure 2.13. To isolate the impact of size, we expand the basic specification to include a quartic in log employment, which yields the "Size" series. Finally, we add the quartic in size, 1-digit industry controls and simple age controls (less than five years and five+ years since listing) to the basic specification to obtain the "Size, Age, and Industry" series in figure 2.13.

The results in figure 2.13 provide a powerful and simple explanation for the trend volatility rise among publicly traded firms. According to the figure, neither size effects alone nor the combination of size, age, and industry effects account for much of the volatility rise.[27] In sharp contrast, simple cohort controls absorb most of the volatility rise for publicly traded firms. Table 2.5 quantifies this point by comparing



Source: Own calculations on COMPUSTAT data.

Notes: Calculations exclude entry and exit. Firm volatility calculated according to equation (6). Average volatility computed on an employment-weighted basis.

Figure 2.13
The Role of Size, Age, Industry and Cohort Effects for Publicly Trade Firms

the longer term change in fitted year effects with and without cohort controls. From 1978 to 1999, for example, the controls for entry cohort absorb 64 percent of the volatility rise among publicly traded firms. Over the 1978 to 2004 period, the trend change in volatility among publicly traded firms is actually negative once we control for entry cohort. In unreported results using LBD data, we find even stronger results—controls for entry cohort absorb 85 percent of the volatility rise among publicly traded firms from 1977 to 2001.

6 Concluding Remarks

Comprehensive micro data reveal that volatility and cross sectional dispersion in business growth rates declined in recent decades. Our preferred measure of firm volatility in employment growth rates (figure 2.6) fell 23 percent from 1978 to 2001 and 29 percent from 1987 to 2001. Our most remarkable finding, however, is a striking difference in volatility and dispersion trends by business ownership status. Among

Table 2.5
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

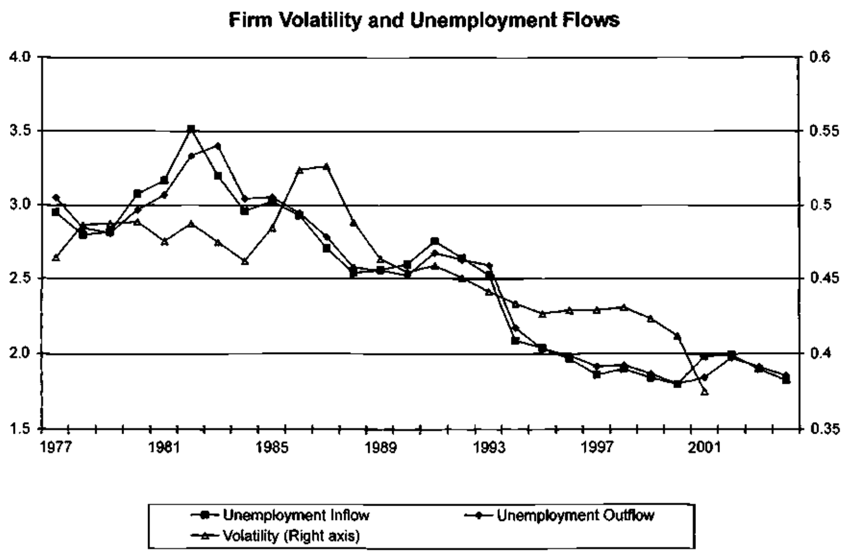
Source: Own calculations on COMPUSTAT data.
Notes: "Initial Volatility" reports estimated year effects in a weighted least squares regression of modified volatility on year dummies, with weights proportional to firm size (z_{it}). The data set consists of an unbalanced panel of firm level observations from 1951 to 2004. "Change in Volatility" reports the change in the estimated year effects ($\Delta\hat{y}$) from the same regression. To quantify the percentage of the volatility change accounted for by cohort effects, we expand the regression to include one-year cohort dummies (year of first listing) and calculate the change in estimated year effects with cohort controls ($\Delta\hat{y}^{CC}$). Lastly, we calculate the "Percentage of Volatility Change Accounted for by Cohort Effects" as $100(\Delta\hat{y} - \Delta\hat{y}^{CC})/\Delta\hat{y}$.

privately held firms, volatility is relatively high but it fell by one–third from 1978 to 2001. Among publicly traded firms, volatility is lower but it rose by three–quarters from 1978 to 1999. This pattern of volatility convergence between publicly traded and privately held businesses prevails for every major industry group.

Our study also provides some proximate explanations for these strong patterns in the data. Employment shifts toward older businesses account for 27 percent or more of the volatility decline among privately held firms. In addition, shifts toward larger businesses played a role in certain industries, particularly Retail Trade. In line with the shifts toward older and larger businesses, the employment-weighted business turnover rate declined markedly after 1978. Finally, simple cohort effects that capture higher volatility among more recently listed firms account for most of the volatility rise among publicly traded firms.

These empirical results suggest a number of interesting questions and directions for future research. Consider, first, the connection between employer volatility and unemployment. Employer volatility can be interpreted as a rough proxy for the intensity of idiosyncratic shocks, a key parameter in unemployment models that stress search and matching frictions. A lower intensity of idiosyncratic shocks in these models leads to less job loss, fewer workers flowing through the unemployment pool, and less frictional unemployment. Motivated by these models, figure 2.14 plots our employment-weighted modified volatility measure against annual averages of monthly unemployment inflow and outflow rates. The figure suggests that secular declines in the intensity of idiosyncratic shocks contributed to large declines in unemployment flows and frictional unemployment in recent decades. More study is clearly needed to confirm or disconfirm this view, and there is surely a role for other factors such as the aging of the workforce after 1980.

Another major development in U.S. labor markets since the early 1980s is a large rise in wage and earnings inequality.[28] One line of interpretation for this development stresses potential sources of increased wage and earnings flexibility: declines in the real minimum wage, a diminished role for private sector unionism and collective bargaining, intensified competitive pressures that undermined rigid compensation structures, the growth of employee leasing and temp workers, and the



Source: Figure 6 for volatility measure and the Current Population Survey.
Notes: Unemployment flows are annual averages of monthly flows, expressed as a percentage of the labor force.

Figure 2.14
Firm Volatility Compared to Unemployment Inflows and Outflows

erosion of norms that had previously restrained wage differentials and prevented wage cuts. Greater wage (and hours) flexibility can produce smaller firm level employment responses to idiosyncratic shocks and smaller aggregate employment responses to common shocks. So, in principle, greater wage flexibility can provide a unified explanation for the rise in wage and earnings inequality *and* the declines in aggregate volatility, firm volatility and unemployment flows. We mention the role of wage flexibility because we think it merits investigation and may be a significant part of the story, not because we believe that greater wage flexibility or any single factor can explain all aspects of longer term developments in wage inequality, unemployment, firm volatility, and aggregate volatility.

The potential role of greater wage flexibility is related to another question raised by our results. In particular, to what extent do trends in firm volatility reflect a change in the size and frequency of shocks, and to what extent do they reflect a change in shock response dynamics? One simple approach to this question is to fit statistical models that allow for nonstationarity in the size and frequency of business level innovations and in the response dynamics to the innovations. Another approach is to identify specific shocks, quantify their magnitude, and investigate whether shock magnitudes and firm level responses to them have changed over time.

Several pieces of evidence point to a major shift in the selection process governing entry into the set of publicly traded firms. Figure 2.13 and table 2.5 above indicate that more than half of the volatility rise among publicly traded firms in recent decades reflects an influx of more volatile firms in later cohorts. Other researchers find that later cohorts of publicly traded firms are riskier in terms of equity return variability, profit variability, time from IPO to profitability, and business age at time of first listing. The shift in the selection process for publicly traded firms is a major phenomenon, in our view, but it does not by itself explain the volatility convergence pattern we have documented or the overall downward trend in firm volatility and dispersion. To appreciate this point, consider a simple selection story that we sketch with the aid of figure 2.15. The figure shows a hypothetical density function for firm level risk and a risk threshold that separates publicly traded from privately held firms. This figure captures, in a highly stylized manner, the notion that publicly traded firms are less risky than privately held ones. Suppose that the risk threshold moves to the right, so that a riskier class of firms now goes public. This shift yields an increase in

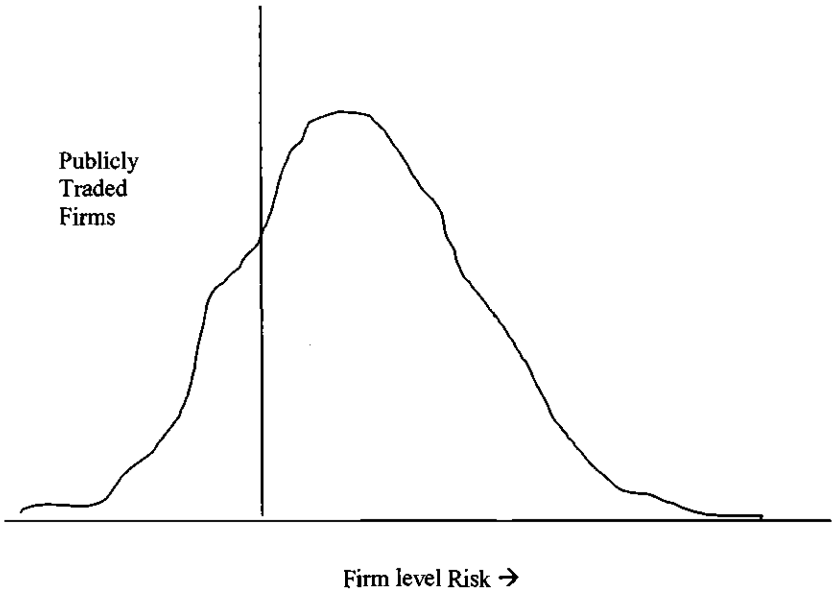


Figure 2.15
Selection on Risk and Firm Ownership Status

average risk among publicly traded firms, but it also produces an increase in average risk among privately held firms and in the share of activity accounted for by publicly traded firms. The latter two implications are at odds with the evidence, at least when risk is measured by firm volatility and activity is measured by employment.

A richer story, with changing selection as one key element, is more consistent with the evidence. As discussed in Section 2, smaller aggregate shocks can readily explain declines in macro volatility and the overall magnitude of firm volatility. In combination with a changing selection process, smaller aggregate shocks can rationalize the volatility convergence pattern we document and the declines in aggregate and average firm volatility. A shift of activity toward older and larger firms may have contributed to changes in the way firms respond to shocks. Shifts in the industry mix away from manufacturing and other industries that traditionally accounted for a large share of publicly traded firms help to explain why the share of employment in publicly traded firms has not risen.

Finally, our results also present something of a challenge to Schumpeterian theories of growth and development. In particular, the sizable decline in average firm volatility that we document coincided with a period of impressive productivity gains for the U.S. economy. This coincidence belies any close and simple positive relationship between productivity growth and the intensity of the creative destruction process, at least as measured by firm-based or establishment-based measures of volatility in employment growth rates. Perhaps there has been a large increase in the pace of restructuring, experimentation, and adjustment activities within firms. Another possibility is that a more intense creative destruction process 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 rapid productivity gains throughout the economy.

Acknowledgments

For many helpful comments on earlier drafts, we thank Chris Foote, Eva Nagypal, the editors, participants in the 2006 NBER Macroeconomics Annual Conference, the CEPR Conference on Firm Dynamics, the Ewing Marion Kauffman—Max Planck Conference on Entrepreneurship and Growth and seminars at the Brookings Institution, the Census Bureau, New York University, and the University of Chicago. We thank Marios Michaelides for excellent research assistance and the Kauffman Foundation for financial support. The views expressed in the paper are those of the authors and do not necessarily represent those of the Census Bureau. The paper has been screened to ensure that it does not disclose any confidential information.

Endnotes

1. The LBD is confidential under Titles 13 & 26 U.S.C. Research access to the LBD can be granted to non-Census staff for approved projects. See www.ces.census.gov for more information. COMPUSTAT, which provides information on publicly traded firms only, has been the primary data source for recent work on firm level volatility.

2. Firm level volatility is calculated from COMPUSTAT data as a moving ten-year window on the standard deviation of firm level growth rates. See equation (5) in section 3.

3. Excess job reallocation equals the sum of gross job creation and destruction less the absolute value of net employment growth. Dividing excess reallocation by the level of employment yields a rate. One can show that the excess reallocation rate is equivalent to the employment-weighted mean absolute deviation of establishment growth rates about zero. See Davis, Haltiwanger, and Schuh (1996).

4. Job flow statistics for the whole private sector are from the BLS Business Employment Dynamics. They are unavailable prior to 1990.

5. Acemoglu (2005), Eberly (2005), and Davis, Faberman, and Haltiwanger (2006) question whether sample selection colors the findings in previous studies of firm level volatility.

6. French stock market reforms in the 1980s considerably broadened the shareholder base for French firms. Thesmar and Thoenig (2004) provide evidence that these reforms led to a rise in the volatility of sales growth rates among listed firms relative to unlisted ones. Their analysis sample contains about 5,600 French firms per year with more than 500 employees or 30 million Euros in annual sales, and that were never owned, entirely or in part, by the French state.

7. Sales data are available in the LBD from 1994. Sales data from the Economic Censuses are available every five years for earlier years. More recent years in the LBD record industry on a NAICS basis.

8. See the data appendix regarding the construction of longitudinal links, which are critical for our analysis.

9. Our COMPUSTAT data are from the same provider (WRDS) as in recent work by Comin and Mulani (2006), Comin and Philippon (2005), and others.

10. See McCue and Jarmin (2005) for details. We extend their methodology to include the whole period covered by the LBD.

11. If we require that matches have positive COMPUSTAT employment *and* positive LBD employment in 1990, then the number of matched CUSIPs drops from 5,716 to 5,035. However, this requirement is overly restrictive in light of our previous remarks about missing COMPUSTAT employment observations, the inclusion of employment from foreign operations in COMPUSTAT, and timing differences between COMPUSTAT and the LBD. For instance, when we relax this requirement and instead allow CUSIPs with positive sales, price or employment to match to LBD firms with positive employment, then the number of matches exceeds 5,700.

12. When we implement (5) using LBD data, we permit the firm to enter or exit at the beginning or end of the ten-year window. This is a small difference in measurement procedures relative to Comin and Mulani (2005, 2006) and Comin and Philippon (2005). A more important difference is that our LBD-based calculations include the pre-public and post-public history of firms that are publicly traded at t but privately held before or after t. As a related point, we do not treat listing and de-listing in COMPUSTAT as firm entry and exit.

13. We thank Eva Nagypal for drawing our attention to this issue.

14. The shorter term response differs, however, as have verified in unreported numerical simulations. For example, a one-time permanent increase in the variance of the distribution of idiosyncratic shocks leads to a coincident permanent increase in the cross sectional dispersion of business growth rates, but it leads to a gradual rise in the average volatility that begins several years prior to the increase in the shock variance and continues for several years afterward.

15. But we do exclude observations with growth rates of 2 and –2, because COMPUSTAT listing and de-listing typically do not reflect true entry and exit by firms. In the LBD-based analysis below, we include observations with growth rates of 2 and –2 (unless otherwise noted), because we can identify true entry and exit in the LBD.

16. A comparison between figures 2.4 and 2.5 reveals that the level of volatility among publicly traded firms is much greater in COMPUSTAT, perhaps because COMPUSTAT activity measures include the foreign operations of multinational firms.

17. Recall that we use all firm-year observations with positive values of z_{it} when computing our basic dispersion measure. That is, we include all continuing, entering and exiting firms. Below, we consider the effects of restricting the analysis to continuing firms only.

18. Foster, Haltiwanger, and Krizan (2005) present related evidence using the Census of Retail Trade. They show that much of the increase in labor productivity in the 1990s in retail trade reflects the entry of relatively productive establishments owned by large national chains and the exit of less productive establishments owned by single-unit firms. See, also, McKinsey Global Institute (2001).

19. While ownership changes can affect firm level longitudinal linkages in the LBD, they do not affect establishment level linkages. See the Data appendix for more discussion of linkage issues.

20. While not a trivial task, we can use the LBD to separately identify and measure firm ownership change, de novo entry and complete firm shutdown. In future work, we plan to explore this decomposition.

21. See the Data Appendix for details about the firm and establishment concepts used in the LBD and the construction of longitudinal links.

22. There is a vast literature on the relationship of business entry, exit, and growth rates to business size and age. See Dunne, Roberts, and Samuelson (1989), Sutton (1997), Caves (1998), Davis and Haltiwanger (1999), and Davis et al. (2005) for evidence, analysis, and extensive references to related research.

23. The precise contribution of shifts in the age distribution to the volatility decline among privately held firms depends on exactly how we carry out the decomposition. Table 2.3, which evaluates volatilities at the 1982 age distribution, implies that the age distribution shift accounts for 27 percent of the volatility drop from 1982 to 2001. Table 2.4, which evaluates volatilities at the 2001 age distribution, reports that the age distribution shift accounts for 19.6 percent of the volatility drop. Both exercises are likely to understate the impact of shifts toward older privately held firms for reasons discussed in the text.

24. The finer size classification breaks the 1,000+ category into 1000–2499, 2500–4999, 5000–9999, and 10,000+ categories.

25. In unreported results, this sample selection requirement has little impact on the overall volatility trend in COMPUSTAT, but it does have an impact on the volatility trends for certain cohorts.

26. The modified volatility series in figure 2.11 are employment weighted. We suppress the 1953 and 1954 values for the 1950s cohort, because they are calculated from only one or two firm level observations. In unreported results, the equal-weighted modified volatility series show a stronger pattern of greater volatility for later cohorts. So does the employment-weighted basic volatility measure.

27. Industry effects play a substantially larger role in table 2.3 (LBD data) than in figure 2.13 (COMPUSTAT data). Unreported results show that much of the difference arises because of different sample periods. In particular, regardless of data set and whether we use a shift-share or regression-based method, industry effects play a substantially larger role from 1982 to 2001 than from 1977 to 2001. Differences between table 2.3 and figure 2.13 in method and data set play a smaller role.

28. See Autor, Katz, and Kearney (2005) for a recent contribution to this literature, a review of major competing hypotheses about the reasons for rising inequality and references to related research.

29. We construct birth and death retiming weights from accurate data on the timing of births and deaths using a conditional logit model. The model includes controls for state, metro, and rural areas and job creation and destruction rates. The model is run separately by 2-digit SIC and for four different 5-year census cycles.

30. There are between 40,000 and 120,000 cases each year. Work by Davis et. al. (2005) shows that business transitions between employer and non-employer status explains some of these cases.

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Data Appendix

A Additional Information about the LBD

This appendix discusses improvements to the LBD that aided the analysis in this paper. The LBD is comprised of longitudinally linked Business Register (BR) files. The BR is updated continuously and a snapshot is taken once a year after the incorporation of survey data collections. The resulting files contain a longitudinal establishment identifier, the Permanent Plant Number (PPN). This identifier is designed to remain unchanged throughout the life of the establishment and regardless of reorganizations or ownership changes. However, there are known breaks in PPN linkages, and PPNs existed only for the manufacturing sector prior to 1982. Jarmin and Miranda (2002a) addressed these shortcomings in the BR files in creating the LBD. Their methodology employed existing numeric establishment identifiers to the greatest extent possible to repair and construct longitudinal establishment links. They further enhanced the linkages using commercially available statistical name and address matching software.

Construction of the longitudinal establishment links is relatively straightforward because they are one to one, and because establishments typically have well-defined physical locations. The construction of firm links requires additional work. Longitudinal linkages of firm identifiers can be broken by the expansion of single location firms to multi establishment entities and by merger and acquisition (M&A) activity. We address the first problem by assigning a unique firm identifier to firms that expand from single to multiple establishments. This process is straightforward because we can track establishments over time. The second problem is harder to resolve, because M&A activity can result in many-to-many matches, e.g., when a firm sells some establishments and acquires others in the same period. We do not directly address this issue in the current paper, but we recognize that it would be interesting to explore the role of M&A activity in greater depth, and we plan to do so in future work.

The combination and reconciliation of administrative and survey data sources in the LBD lead to a more serious problem that we have addressed in the current analysis. Early versions of the LBD contain a number of incorrectly timed establishment births and deaths. To see how this timing problem arises, recall that the LBD is a longitudinally linked version of the Business Register. Although the primary unit of observation in the BR is a business establishment (physical location), administrative data are typically available at the taxpayer ID (EIN) level. As the vast majority of firms are single establishment entities, the EIN, firm, and establishment levels of aggregation all refer to the same business entity. Business births typically enter the BR from administrative sources. Outside of Economic Census years, however, the Census Bureau directly surveys only large births, as measured by payroll. In Economic Census years, all establishments of "known" multi location firms are directly surveyed. A subset of larger single location businesses are canvassed as well.

The Census Bureau separately identifies the individual establishments of multi-establishment companies based on primary data collections from the Economic Census and certain annual surveys such as the Company Organization Survey and the Annual Survey of Manufacturers. Since a much larger portion of firms and establishments are surveyed in Economic Census years (years ending in "2" and "7"), the Economic Census becomes the primary vehicle by which the Census Bureau learns about establishment entry and exit for smaller multi-unit firms. This information is then incorporated into the LBD. The implication is that the unadjusted LBD files show large spikes in establishment births and deaths for multi-unit firms in Economic Census years. Many of those births and deaths actually occurred in the previous four years.

We retime these incorrectly timed deaths and births following a two-phase methodology, described more fully in Jarmin and Miranda (2005). The first phase uses firm level information contained in the LBD to identify the correct birth and death years for as many establishments as possible. The second phase adapts an algorithm developed by Davis, Haltiwanger, and Schuh (1996) to randomly assign a birth or death year for those cases that cannot be resolved in phase one. The randomization procedure is constrained so that the temporal patterns of births and deaths for retimed cases match those for the accurately timed births and deaths that we observe directly in the data (single-unit births and establishment births in large multi-unit firms that are directly canvassed).[29]

Finally, the LBD contains a substantial number of establishments that appear to become inactive for a period of time (Jarmin and Miranda 2002b). That is, the establishment is active in period $t - 1$ and $t + 1$ but not in period t.[30] These gaps lead to possibly spurious startups and shutdowns. In this paper, we take a conservative approach by eliminating these establishment-year observations in the entry and exit computations. Our goal in doing so is to focus on true entry and exit.

B COMPUSTAT-LBD Employment Comparisons

The top panel in figure 2A.1 compares log employment levels between COMPUSTAT and the LBD data sources for a matched set of publicly traded firms. The lower panel compares five-year growth rates, calculated according to equation (4). Here, we restrict attention to matched firms that have positive employment in the LBD and COMPUSTAT. Much of the mass is concentrated along the 45 degree line in the top panel, but there are clearly many large discrepancies between the two data sources. The simple correlation of log employment levels is 0.89 on an unweighted basis and 0.83 on an employment-weighted basis. The standardized employment difference, measured as LBD employment minus COMPUSTAT employment divided by the average of the two, has an unweighted median value of –13 percent and an unweighted mean of –26 percent . The weighted values are –25 percent for the median and –30 percent for the mean. The lower panel shows a weaker relationship for growth rates, with a correlation of 0.64 unweighted and 0.54 weighted. Lower values for the weighted correlations probably reflect bigger discrepancies for multi-national firms with significant global operations.

In short, the results in figure 2.1 indicate that COMPUSTAT measures of firm level activity contain considerable measurement error, if the goal is to measure the U.S. domestic operations of publicly traded firms. Despite the large COMPUSTAT-LBD differences in employment levels and growth rates, the two data sources produce similar trends in firm volatility measures, as seen by comparing figures 2.4, 2.5, and 2.7.

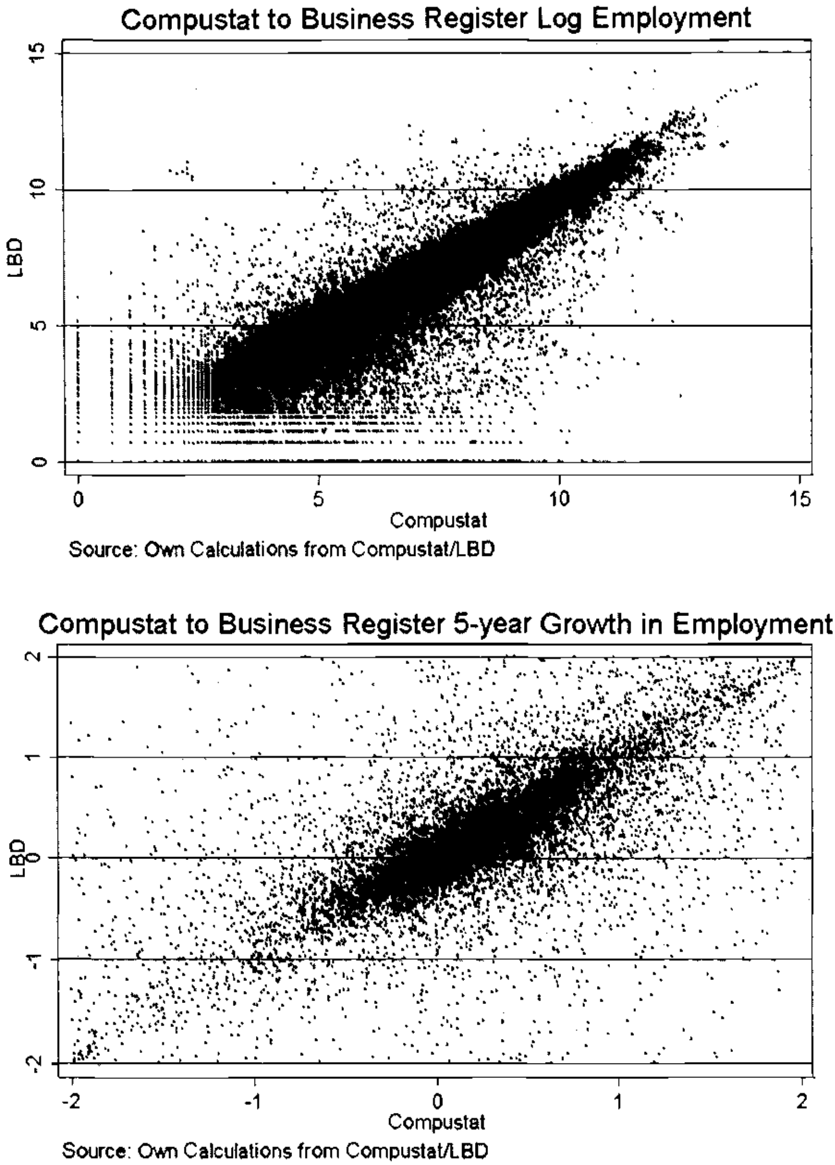

Figure 2A.1
Comparisons of Employment levels (logs) and Employment Growth Rates for LBD and COMPUSTAT Matched Firms (Pooled 1994–2001)

Comment

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Sixteen years ago, Steven Davis and John Haltiwanger's paper for the *NBER Macroeconomics Annual* was among the first to use firm-level data to study employment fluctuations. The focus of the current paper, written with Ron Jarmin and Javier Miranda, is on a different piece of the employment picture. The authors argue that during the past two decades, employment levels at individual firms and establishments have become more stable. Their preferred measure of firm volatility for the U.S. private sector, displayed in figure 2.6, declines by about one-quarter from 1978 to 2001. I am confident that like Davis and Haltiwanger (1990), this thoughtful paper will influence both empirical and theoretical work long after its publication.

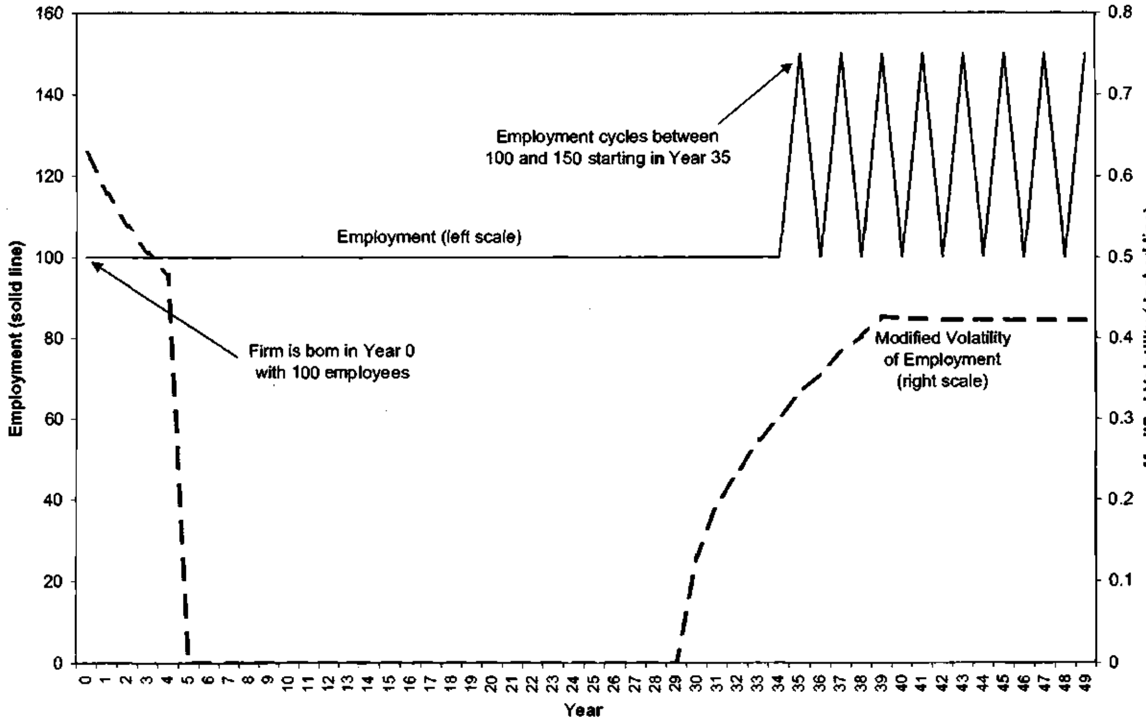
In this comment, I will explore three main themes, with the first two involving measurement issues. I begin by developing some intuition for the author's preferred volatility statistic. This intuition illustrates why their results are admittedly sensitive to the treatment of firm entry and exit. My second point involves the relationship between microeconomic volatility and business cycles. The paper does an excellent job of highlighting why this relationship is interesting; some theoretical models predict that both types of volatility should decline as an economy develops, while other models claim that macro and micro volatility should move in opposite directions. My own view is that without taking account of micro-level adjustment costs, setting down the stylized facts in this literature will be difficult. Finally, my third point is that it seems highly likely that some decrease in idiosyncratic volatility has indeed occurred, based on the results of this paper and some worker-based data cited in the paper. This decrease has no doubt contributed to the decline in the U.S. unemployment rate during the past two decades. As a result, the authors' research agenda may prove integral to answering a question on the minds of many policymakers: Why has the natural rate of unemployment fallen so much?

1 Measuring Firm-level Volatility and Dispersion

Economists discuss employment volatility all the time. However, typically the volatility occurs in some going concern, like an entire economy, or a big, publicly traded firm. The authors' data are distinguished by the inclusion of all firms in the United States (a monumental accomplishment) and most of these firms are small, with high entry and exit rates. To probe these data, the authors apply some previous variance statistics and develop a new, preferred one, "modified firm-level volatility" (equation 6). The new statistic allows data from even short-lived firms to contribute to overall volatility averages.

To gain some intuition for the modified volatility statistic, I worked through some examples using simulated data from individual firms. Figure 2.16 presents data from one such firm. The firm is born with 100 employees in year 0. Employment (the solid line) remains constant at 100 until year 35, when it begins to cycle annually between 100 and 150 employees. Modified volatility (the dotted line) starts out high at 0.63, reflecting the high "growth rate" registered in the birth year ($\gamma = 2$). By year 5, the rolling standard deviation moves past this initial growth rate, so volatility falls to zero, as we would expect for a firm with constant employment. In period 30, modified volatility begins to rise in anticipation of the cycling phase, because this statistic is a centered standard deviation of past, current, and future γ's. During the cycling phase, the firm's γ's (not shown) alternate between –0.4 and 0.4, and modified volatility stabilizes to about 0.42.[1]

I would think that a firm that cycles annually between 100 and 150 employees would have a lot of jittery employees. If this level of volatility reflected the stability of employment in the United States, most of us would arrive at work each day fearing pink slips on our desks! According to figure 2.6, however, employment-weighted modified volatility in the U.S. private sector is greater than 0.4 almost every year from 1977 and 2001. The reason for this high measured volatility is entry and exit. Note that for our sample firm, the highest modified volatility comes in the year immediately following its birth—thanks to the $\gamma = 2$ recorded in its initial year—even though employment is constant for the firm's first 35 years.



Note: Modified volatility is calculated using Equation 6 of the paper.

Figure 2.16
Employment and Modified Volatility for a Simulated Firm

Just as interesting is what happens when a firm is short-lived, so that it contributes both a birth and a death to the data. In these cases, the modified volatility statistic may have problems distinguishing between short-lived firms that are truly volatile and those that are not. I calculated modified volatility for two simulated firms that each operated for four years. In one firm, the employment sequence was 100, 200, 300, 400, 0 while a second, less volatile firm had employment of 100, 100, 100, 100, 0. The modified volatility statistic for the first firm was indeed larger than that of the second, but not by much. In each year of the data, the first firm's modified volatility was 1.19, but the stable firm's statistic only marginally smaller, at 1.12. The likely reason for this similarity is that the γ's of 2 and –2 that bookend both of these firms' histories are dominating their modified volatility statistics, so that the statistic is unable to distinguish much difference in volatility between them.[2]

The implication of these simulations is that fluctuations in the number of births and deaths in the economy are likely to have a large impact on economywide volatility that may not accurately reflect underlying theoretical concepts. Indeed, the authors' figure 2.8 shows that excluding births and deaths causes the average level of modified volatility to decline by about one-third. More importantly for our purposes, the authors point out that the *decline* in volatility among privately held firms also becomes less pronounced, relative to their preferred figure 2.6. In fact, modified volatility for the entire economy is essentially flat over the sample period when entry and exit are left out.

The issue is just as important for the other variance statistic discussed by the authors, the cross-sectional distribution of γ's in any particular year. To make a trivial point, both an entry γ of 2 and an exit γ of –2 get larger in absolute value when they are squared for a calculation of cross-sectional standard deviation. But squaring shrinks the contribution of firms with more modest growth rates ($\gamma < 1$). As a result, births and deaths of even small firms can have exceptionally large influences on the time-series pattern of cross-sectional dispersion. It is not hard to come up with examples in which the entry or exit decision of a tiny firm makes a big difference for employment-weighted dispersion in a sector that includes many large firms.[3]

The authors make a strong case that entry and exit should not be ignored when discussing idiosyncratic volatility, despite the associated measurement difficulties. When Wal-Mart enters a market and pushes out smaller, more volatile firms, employment volatility in the labor market declines in part because Wal-Mart is less likely to likely to go out of business than the stores it replaces. My concern is that I don't have a good feel for the *quantitative* impact that entry and exit should have on measures of economywide volatility. There is no obvious way to answer this question, given the difficulty of translating the infinite percentage changes in employment that occur upon entry and exit into some growth rate that can contribute to an economywide volatility average. The authors' growth rate (γ) equals 2 upon an entry, but why shouldn't this number be 4? Or 1? By implication, how do we know that the author's preferred figure 2.6 does a better job of informing theoretical work on this topic than figure 2.8, where entry and exit are excluded?

2 Aggregate Shocks, Idiosyncratic Variance, and the Great Moderation

My second point is that the empirical separation of trends in aggregate vs. idiosyncratic volatility is likely more difficult that it would appear at first glance. In recent years, there has been an explosion of theoretical work on firm-level volatility. Among other things, this work explores the implications of changes in research and development intensity, better diversification through financial markets, and a wider basket of potential inputs to production. This research also asks how changes in idiosyncratic volatility are likely to affect volatility at the aggregate level. For example, could microeconomic factors leading to higher or lower firm-level volatility help explain the Great Moderation in the U.S business cycle since the mid-1980s?

This research generally concerns the volatility of desired employment at firms, but *desired* employment differs from the *actual* employment we see in data when there are firm-level adjustment costs. One of the most important lessons we have learned from micro-level employment data in the past two decades is that these costs should not be ignored. Changes in either employment or capital stocks on the micro level are usually much less frequent and much larger than we would expect under convex adjustment costs (or no costs at all). This pattern is typically explained by some non-convexity in adjustment costs, of which the simple (S,s) model is the best-known example.[4]

Non-convex adjustment costs draw a sharp distinction between the observed level of employment at firms and the desired level, with the latter denoting the employment level that would obtain if adjustment costs were momentarily suspended. In turn, the distinction between actual and desired employment makes it difficult to isolate aggregate shocks in the data. This is because only a few firms are likely to adjust actual employment when an aggregate shock occurs, even though the shock may affect desired employment at all firms in the same way. Think of a negative aggregate shock that reduces desired employment for all firms. In an (S,s) world, this shock will push some firms over the "reduce employment" boundary, so they will reduce employment a great deal. The other firms just move closer to this boundary, remaining inside the (S,s) inaction region.

What is more, the presence of non-convex adjustment costs can confuse the relationship between aggregate volatility and firm-level volatility. Consider again the implications of a negative aggregate shock. The fact that some firms are pushed over the reduce-employment boundary shows up in the data as an increase in the dispersion of firm-level employment changes. After all, some firms have adjusted employment a great deal, while others have kept employment stable.

This empirical regularity is important for interpreting Davis and Haltiwanger's 1990 paper, one of the first to explore the relationship between aggregate and firm-level volatility. Using a dataset that included establishment-level data from the manufacturing industry alone, that paper found that the recessions of 1975 and 1982 were periods of intense reallocation in the manufacturing sector, as measured (for example) by a measure of dispersion in the absolute value of employment changes at the microeconomic level This led them and a number of other 1990s authors to explore the possibility that recessions and interfirm employment reallocation were theoretically linked, perhaps because recessions were in a time of low aggregate productivity (so that the opportunity costs of suspending production for reallocation fell in recessions). The recessions-as-reallocations theory suffered when confronted with other data, however. In other countries (Boeri 1996) or in non-manufacturing industries (Foote 1998), reallocation often looked procyclical, as the cross-sectional distribution of employment growth rate spread out in booms, not recessions. A simple explanation for this discrepancy is that an intense aggregate shock *in any direction* will cause measured microlevel dispersion to rise in an (S,s) world. If the data covers a period of intense positive shocks, microeconomic dispersion will look procyclical. If instead the most intense aggregate shocks are negative, then dispersion will look countercyclical.

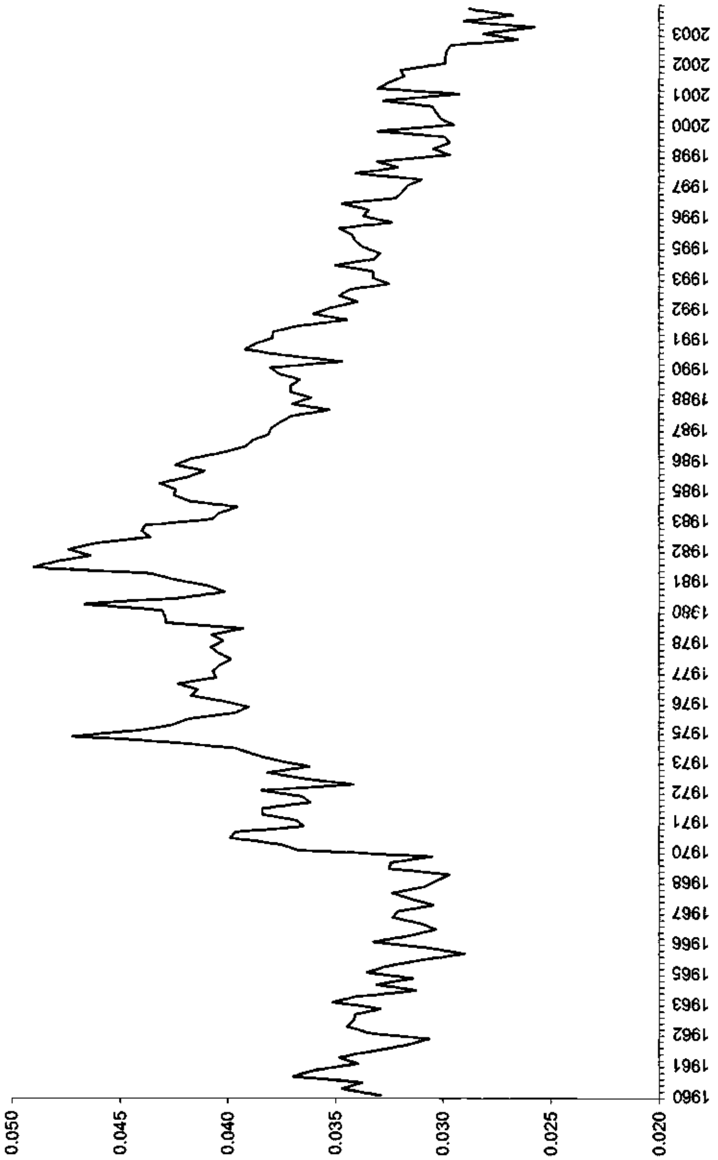
Now consider the more recent lines of inquiry into micro and macro volatility. Section 2 of the paper states that there is a "simple mechanical reason to anticipate that micro and macro volatility will trend in the same direction." I would elaborate on this statement, adding that under non-convex adjustment costs, there is a mechanical reason why a period of less-intense aggregate shocks will also be periods of lower idiosyncratic variation. So, theories that predict that micro and macro volatility trend in the same direction may be "vindicated" by the data, even if there is no underlying relationship between business cycles and idiosyncratic volatility in the desired employment of firms.

A unifying theme of my first two points is that asking simple questions of microeconomic data can be harder that it seems, due in part to the granular nature of employment change at the microeconomic level. Rather than curse our fate at having to deal with the associated measurement issues, I think we should instead be encouraged to continue to develop empirical models that highlight distinctions between desired and actual employment. Those who would test recent theories on the relationship between aggregate and idiosyncratic volatility will undoubtedly find these models useful.

3 Firm-level Idiosyncratic Variance and Workers Flows

Despite my concerns regarding measurement issues, I am quite comfortable with the idea that some decline in idiosyncratic volatility has recently occurred. As the authors point out, their results dovetail nicely with worker-based data. Their figure 2.14 correlates firm-level volatility with flows into and out of unemployment, with the latter two flows expressed as fractions of the labor force. I believe that the point can be made more forcefully by looking at the data in a different way. My figure 2.17 graphs the average monthly probability that an employed worker will separate into unemployment, as calculated by Robert Shimer. The data are quarterly averages of monthly rates from 1960:1 to 2004:4. Focusing on the separation rate is useful because this rate is closely related to reallocational intensity in search-and-matching models of the labor market (Pissarides 2000, Chapter 1). The main feature of the graph is the low-frequency rise and fall in separations after 1970. Because the trend unemployment rate is essentially the ratio of the separation rate to the sum of separation and finding rates, this movement in separations is a prime determinant of low-frequency movements in the overall unemployment rate as well.[5]

As the authors point out, one potential source for movements in separations is worker demographics. The peak year for baby boom births is



Source: Robert Shimer (http://home.uchicago.edu/~shimer/data/flows/sep.dat)

Figure 2.17
Job Separation Rate

1957, so a lot of young people—with high separation rates—are entering the labor market near the time when separations are highest. Yet movements in separations are probably too large to attribute to demographics alone, as attempts to link recent trends in overall unemployment solely to demographics have typically failed (Katz and Krueger 1999). Something else besides demographics must also be causing the separation rate to move, and, by extension, driving the trend in the overall unemployment rate. But what?

A great deal of ink has been spilled on sources of the recent decline in the natural unemployment rate, most of it focused on the question from the worker's point of view. I think it likely that at least part of the answer will be found in firm-side data of the type that the authors employ. In light of this, the results in the paper's table 2.2 are especially tantalizing. At least among privately held firms, declines in volatility from 1978 to 2001 are strikingly similar across industries, ranging from a low of 22.6 percent in Mining to 38.3 percent in Wholesale Trade. This similarity could rule out some explanations for declining volatility while supporting others.

4 Conclusion

The four authors of this paper are to be commended for the care in which they have constructed these data and the imagination they have used in analyzing them. As their research agenda develops, I would press them to clarify the measurement issues I have discussed as well as further explore the links between firm-side data to unemployment trends. Like many in both the policy and academic worlds, I will be interested to learn what they find.

Endnotes

1. The volatility statistic would be of course be invariant to scaling the firm's employment history by some constant factor, which would leave the sequence of γ's unchanged.

2. A firm in existence for only one year contributes two observations of 2.83 to modified volatility, no matter what its size.

3. Consider an industry with ten firms. Nine of the firms have employment weights of 1,000 (that is average employment in t and $t-1$ of 1,000), and their γ's are distributed between –0.02 and 0.02 (three with $\gamma = -0.02$, three with $\gamma = 0.02$, one with $\gamma = -0.01$, and two with $\gamma = 0.01$). The tenth firm has four employees, and either keeps employment constant ($\gamma = 0$, employment weight = 4) or drops employment to zero ($\gamma = -2$, employment weight = 2). If the tenth firm keeps employment constant, the employment weighted

standard deviation of the ten firms will equal 0.0182. If the tenth firm exits, this statistic nearly doubles, to 0.0363.

4. In an (S,s) world, firms keep the deviation of desired-from-actual employment bounded, changing employment only when this deviation crosses either the "S" or "s" boundary. A generalization of the (S,s) model is the upward-sloping hazard model, which states that the probability ("hazard rate") for employment adjustment rises as the deviation of desired-from-actual employments gets larger (Caballero, Engel, and Haltiwanger 1997). The (S,s) model is an extreme version of this framework, in which the hazard rate is 0 inside the (S,s) region and 1 outside of it. To my knowledge, there is little disagreement over whether non-convex adjustment costs are important at the micro level, although there is considerable disagreement over whether these non-convexities matter for macroeconomic dynamics (Thomas (2002), Veracierto (2002)) as well as disputes over the precise way in which micro-level models should be specified and estimated (Cooper and Willis (2004), Cabellero and Engel (2004)).

5. Indeed, Shimer (2005) argues that business cycle variability in unemployment should be credited to the finding rate, not the separation rate, in contrast to previous research. It seems reasonable that lower frequency movements would then be driven in large part by the separation rate.

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Comment

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1 Introduction

The work of Davis, Haltiwanger, Jarmin, and Miranda (henceforth, DHJM) is a very informative piece of work that brings new and more comprehensive data to the active research area of business volatility. Just last year at the Macroeconomics Annual, Comin and Phillipon (henceforth, CP) were examining the change in business volatility that took place in recent decades and its relation to the change in aggregate volatility. DHJM confirm the findings of CP that the volatility of publicly-held firms increased recently, but show that the features of the COMPUSTAT data used by CP do not generalize to all firms, since there are important differences in the business volatility trend of publicly-traded versus privately-held firms.

To show just how exhaustive the LBD data DHJM use are, in table 2.6, I compare the employment numbers from the Current Employment Statistics, the Bureau of Labor Statistics' most comprehensive survey of payroll employment in private nonfarm industries, for 1980, 1990, and 2000, with the employment numbers for the same segment of the economy from the LBD. As can be seen, in all years, the LBD covers essentially all employment in private nonfarm industries, of which only a little over a quarter takes places in publicly-traded firms.

I view the DHJM piece as the beginning of an exciting new research program using the rich data available in the LBD. In my discussion, I would like to offer some suggestions as to how one might use these data to address questions that are at the core of macroeconomic research today. First, I discuss whether the distinction between publicly-traded versus privately-held businesses matters for macroeconomics and whether the LBD data are well-suited to study this distinction further. Second, I discuss the macroeconomic implications of the decline in

Table 2.6
Comparison of Private Nonfarm Employment in All Firms and in Publicly-Traded Firms for Selected Years from the Current Employment Statistics and the Longitudinal Business Database

Year	CES Private Nonfarm Employment	LBD as Fraction of CES	Publicly-Traded LBD As Fraction of CES
1980	74,695,000	97.3%	28.2%
1990	91,324,000	100.6%	25.1%
2000	110,644,000	102.4%	26.6%

Source: CES from Bureau of Labor Statistics, LBD from DHJM.

business volatility and relate it to the decline in aggregate volatility that has taken place recently. Finally, I offer some thoughts on how one might interpret the decline in business volatility observed in the LBD data.

2 Ownership Structure: Should Macroeconomists Care?

DHJM repeatedly stress in their paper the difference in the volatility trends of publicly-traded versus privately-held firms. For example, in their table 2.2, DHJM document that the volatility of employment growth in publicly-traded firms and in privately-held firms has shown very different trends between 1978 and 2001: The first increased by 55.5 percent while the second declined by 33.4 percent. Given the predominance of privately-held businesses, the overall volatility of business growth rates has also declined over the same period by 22.9 percent.

At an elementary level, these divergent trends mean that there has been a change in the way publicly-traded businesses are selected from the universe of all businesses. This phenomenon has received considerable attention lately in the finance literature. Campbell, Lettau, Malkiel, and Xu (2001) document a more than two-fold rise in the idiosyncratic variance of stock returns between 1962 and 1997 and speculate that some of this increase could have been due to the replacement of conglomerates with companies focused on a single economic activity and the tendency of firms to issue stocks earlier in their life-cycle. Fama and French (2004) provide evidence that not only did new listings become more numerous since 1980, but their profitability became progressively more left skewed and their growth became more right skewed.

This change in selection can have important macroeconomic consequences. For example, if the nature of financing affects investment decisions, then the easier access of younger and smaller businesses to public financing could impact aggregate investment activity. Or, if the nature of financing affects innovation and thereby productivity growth at the firm level, then easier access to public financing would affect aggregate productivity growth. While these are interesting hypotheses to entertain, a limitation of the LBD data used by DHJM is that they do not contain information on the investment or innovation activity of businesses, only on their employment and payroll. So macroeconomists have many potential reasons to care about the changing ownership structure, but it is not clear that the LBD data are well-suited to study these issues further.

3 Macro Effects of the Business Volatility Decline

As is well-known by now, there has been a considerable decline in the volatility of most aggregate variables in recent decades (often referred to as the "Great Moderation"), though there is disagreement about the exact timing and nature of this decline (McConnell and Perez-Quiros 2000, Stock and Watson 2002, and Blanchard and Simon 2001). I document the decline in the volatility of the growth of private nonfarm employment—the most relevant aggregate measure for the LBD data—in figure 2.18. Panel a) plots the 12-month growth rate of private nonfarm employment and panel b) shows the standard deviation of the 12-month growth rate using a ten-year moving window. Clearly, the volatility of private nonfarm employment has declined from the 1940s to the 1960s, picked up in the 1970s and then declined again since 1980.

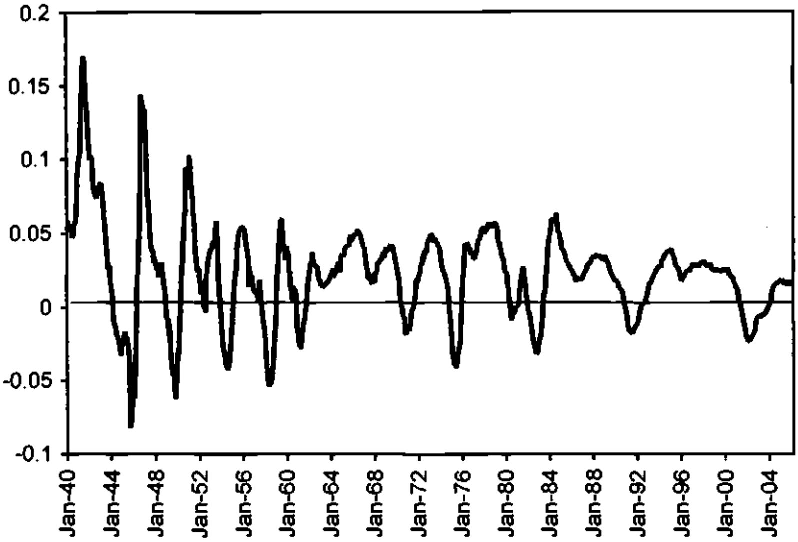
How does this aggregate trend relate to the trend in idiosyncratic volatility? To clarify ideas, let us consider the simplest model of business growth rate and assume that firm j's growth rate at time t is determined by an aggregate growth shock, Z_t, with variance σ^2_{zt}, and an idiosyncratic growth shock, ε_{jt}, with variance σ^2_{jt}, that is independent across firms and of the aggregate shock:

$$\gamma_{jt} = \beta_t Z_t + \varepsilon_{jt}. \tag{1}$$

Assuming that there are N firms in the economy, the aggregate growth rate is

$$\gamma_t = \sum_{j=1}^{N} \alpha_{jt}\gamma_{jt} = \beta_t Z_t + \sum_{j=1}^{N} \alpha_{jt}\varepsilon_{jt}, \tag{2}$$

a) 12-month growth rate of private nonfarm employment between 1940 and 2006.



b) Standard deviation of the 12-month growth rate of private nonfarm employment using a 10-year moving window between 1945 and 2001.

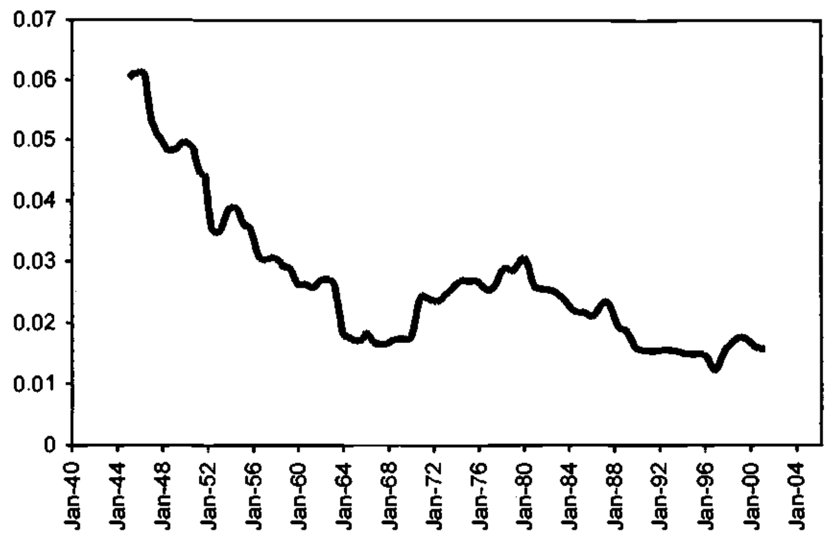


Figure 2.18
Volatility of the Growth Rate of Private Nonfarm Employment
Source: CES from Bureau of Labor Statistics.

where α_{jt} is the share of firm j in total employment. The variance of the aggregate growth rate then is

$$\operatorname{var}(\gamma_t)=\beta_t^2\sigma_{zt}^2+\left(\sum_{j=1}^{N}\alpha_{jt}^2\right)\sigma_{ft}^2. \tag{3}$$

The role of idiosyncratic variability in influencing aggregate variability is thus determined by the size of the term $\Sigma_{j=1}^{N}\alpha_{jt}^2$. If all businesses are of the same size, then $\Sigma_{j=1}^{N}\alpha_{jt}^2 = 1/N$. With close to 5,000,000 firms in the economy, the term $\Sigma_{j=1}^{N}\alpha_{jt}^2$ vanishes and

$$\operatorname{var}(\gamma_t)=\beta_t^2\sigma_{zt}^2, \tag{4}$$

so that idiosyncratic shocks play no role in determining the variability of the aggregate growth rate.

Of course, not all firms in the economy are of the same size, and the presence of large firms could influence the above calculations, as argued by Gabaix (2005). A simple back-of-the-envelope calculation based on the 50 largest U.S. private employers as reported by Fortune 500 implies, however, that even if one accounts for large employers, the term $(\Sigma_{j=1}^{N}\alpha_{ft}^2)\sigma_{ft}^2$ contributes at most 10 percent to the variance of aggregate employment growth. So, to understand changes in aggregate volatility, it is critical to understand the part of aggregate volatility that comes from aggregate disturbances.

In the context of the present paper, though, isolating aggregate disturbances is not straightforward to do, since DHJM measure weighted mean firm-level volatility, which in the above framework can be expressed as

$$\sum_{j=1}^{N}\alpha_{jt}\operatorname{var}(\gamma_{jt})=\beta_t^2\sigma_{zt}^2+\sigma_{ft}^2. \tag{5}$$

Thus the DHJM measure is a sum of the idiosyncratic risk term σ_{ft}^2, which has limited influence on aggregate volatility, and of the aggregate disturbance term, $\beta_t^2\sigma_{zt}^2$. To isolate the aggregate component (or more generally comovement among firms in an industry, or region), a possible econometric specification could be

$$\gamma_{jt}=f(d_j, d_t, X_{jt}, \gamma_{jt-1}, \varepsilon_{jt}), \tag{6}$$

where d_j is a firm fixed effect, d_t is a time effect identifying time trends in growth rates common across firms, and X_{jt} are time-varying firm characteristics, such as size and age.

With the rich data available in the LBD, by extracting a common component across different industries and studying its volatility, one could answer many interesting questions relating to the Great Moderation (GM). For example, was there a GM in all segments of economy? When did the GM start? Did it start at the same time in all segments of economy? Is the GM related to jobless recoveries as hypothesized by Koenders and Rogerson (2005)? Was the GM due to falling correlation between segments of the economy?

The last question of falling correlations among segments of the economy is all the more relevant, since not only could this account for the fall in aggregate volatility, but there is also evidence supporting its empirical validity. Assume that the aggregate growth shock, Z_t, in the above framework is composed of two separate fundamental shocks (say, to different segments of the economy):

$$Z_t = \beta_1 Z_{1t} + \beta_2 Z_{2t}. \tag{7}$$

Then

$$\sigma_{zt}^2 = \beta_1^2 \operatorname{var}(Z_{1t}) + \beta_2^2 \operatorname{var} Z_{2t} + 2\beta_1\beta_2 \operatorname{covar}(Z_{1t}, Z_{2t}), \tag{8}$$

so a fall in the correlation of the two shocks would immediately imply a fall in the variance of the aggregate component.

The empirical relevance of this falling correlation is suggested by the fact that the correlation among the eight major private nonfarm sectors has fallen since the early 1980s, exactly the same period that aggregate volatility has fallen. To show this, in figure 2.19, I plot the average pairwise correlation between the 12-month growth rate of employment in eight major private nonfarm sectors using a ten-year moving window, both weighted by sectoral employment and unweighted.

Of course, the most important outstanding question about the Great Moderation is whether it was due to a change in the size of the shocks, i.e., a result of smaller exogenous or policy shocks, or to a change in the transmission mechanism from shocks to outcomes that took place due to a shift from goods to services, to better inventory management, to innovations in financial markets, or to a changing composition of the workforce. Putting this question into the context of the above simple model, did var(γ_t) decline because σ_{zt}^2 declined or because β_t declined?

With regards to this question, it is not immediately clear how the microdata of the LBD can help, since just as the aggregate data, they

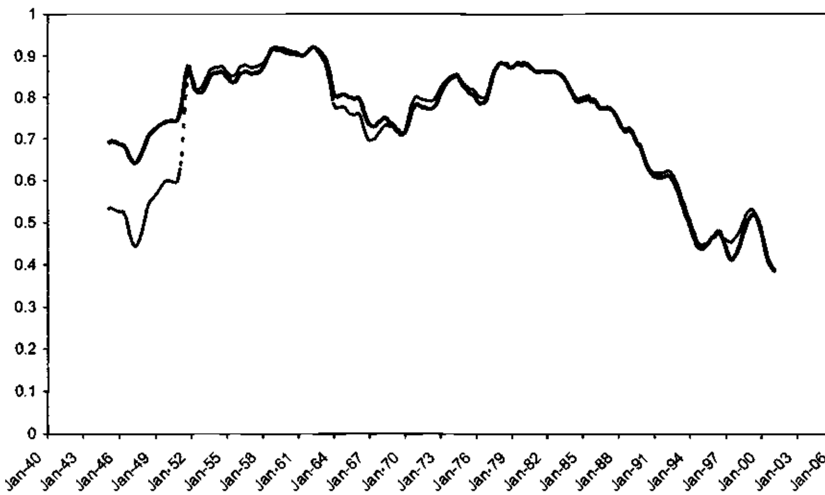


Figure 2.19
Average Pairwise Correlation between the 12-Month Growth Rate of Employment in the Eight Major Private Nonfarm Sectors, Ten-Year Moving Window, Unweighted (Thick Line) and Weighted (Dotted Line)
Source: CES from Bureau of Labor Statistics.

contain a joint $\beta^2_t\sigma^2_{zt}$ term. In fact, due to the lack of identification, there is no purely statistical method that allows one to disentangle the effects of smaller shocks and of changing transmission, so one needs to look at the data through the lens of a theoretical model to make identification possible. Nonetheless, a better understanding of the time path and nature of the Great Moderation by using micro data could be very informative in shaping our thinking about this important macroeconomic question.

4 Interpreting the Decline in Business Volatility

DHJM state that in their paper they are giving "empirical indicators for the intensity of idiosyncratic shocks." This is one possible interpretation of their results. Even if one accepts that the overall decline is not simply a result of a change in the composition of observables among U.S. businesses, the decline in the volatility of the growth rate of an individual producer could be due to a decline in the shocks that affect this producer or to a change in the producer's environment and/or behavior. This is the same issue of shocks versus transmission that arises with regards to aggregate volatility.

To demonstrate this distinction and to highlight the usefulness of looking at the data through the lens of a theory, let us consider a simple model. To be able to talk about employment determination and employment volatility at the firm level, one needs a model of employment determination with frictions. One such model is due to Bentolila and Bertola (1990), where the frictions take the simple form of adjustment costs.

Assume that there is a monopolist firm that maximizes its discounted profits using discount rate r and at each instant faces a downward-sloping demand function, $Q_t = Z_t P_t^{-1/(1-\mu)}$, where $0 < \mu < 1$, Q_t is the firm's output at time t, P_t is the price it charges at time t, and Z_t is a stochastic demand shock, where Z_t follows a geometric Brownian motion, $dZ_t = \theta Z_t dt + \sigma Z_t dW_t$. Assume that output is linear in labor, the only input into production, which has a fixed flow cost of w.

There is exogenous worker attrition at rate δ. In addition to this attrition (for which the firm pays no adjustment cost), the firm can decide to hire or fire workers. If the firm fires workers, then it has to pay a firing cost of c_f per unit of labor. If the firm hires workers, then it has to pay a hiring cost of c_h per unit of labor.

In this environment, it is straightforward to show that the optimal policy of the firm is to keep the ratio L_t/Z_t in an interval $[l_h, l_f]$, so that the firm starts hiring if L_t is to fall below $l_h Z_t$ and starts firing if L_t is to exceed $l_f Z_t$. For a given set of model parameters, one can then calculate the optimal inaction interval $[l_h, l_f]$, and simulate the stochastic path of the firm's employment over time. Performing such a simulation given an annual attrition rate of $\delta = 0.10$ and a demand volatility parameter of $\sigma = 0.15$ and calculating the DHJM measure of firm-level employment volatility gives a volatility measure of 0.108 as can be seen in the first column of table 2.7.[1]

Now let us assume that we see the volatility of the same firm's employment decline to 0.084. What could explain such a decline? It turns out that there are several possible explanations. First, as column 2 of table 2.7 shows, the decline in firm-level volatility could be due to a decline in the size of the demand shocks, with σ being reduced from 0.15 to 0.10. This would be a shocks-based explanation. Second, as column 3 of table 2.7 shows, the same decline could be due to a change in δ, the exogenous attrition rate, from 0.10 to 0.05. Such a decline in the exogenous attrition rate in the 1980s and 1990s could accompany an aging of the workforce that took place as the baby boom generation became older, since it is well-known that older workers have much lower rates

Table 2.7
DHJM Volatility Measure and Adjustment Frequency for Different Parameter Specifications in the Employment Determination Model with Adjustment Costs

	Benchmark Specification $\delta = 0.10$ $\sigma = 0.15$	Smaller Shocks Hypothesis $\delta = 0.10$ $\sigma = 0.10$	Baby Boom Hypothesis $\delta = 0.05$ $\sigma = 0.15$
DHJM volatility	0.108	0.084	0.084
Adjustment frequency	8.5 weeks	6 weeks	15.4 weeks

of exogenous attrition than younger workers. This, of course, would be a transmission-based explanation, since here the change in the firm's environment led to a decline in firm-level volatility.

So it is clear that the decline in firm-level volatility need not necessarily imply a reduction in the size of the shocks that the firm experiences, rather it could be due to other changes in the firm's environment. The advantage of having an explicit model is that it can give us ways to disentangle the two possible reasons for the decline in volatility. In particular, in the above simple model, the two sources of the decline in firm-level volatility could be distinguished by looking at the average time between adjustments of the firm's workforce. In the case of smaller shocks, the average time to adjust declines, since now the firm faces less risk and is willing to take advantage even of small changes in demand (i.e., the region of inactivity shrinks). In the case of lower exogenous attrition due to the baby boomers getting older, the average time to adjust increases, since now the firm needs to do replacement hiring less often.

Of course, these simple calculations are only demonstrative, since they rely on an easily calculable partial-equilibrium model with some restrictive assumptions, but they demonstrate how one might use a theoretical model to think about the rich data studied in DHJM. Campbell and Fisher (2004) develop a dynamic stochastic general equilibrium model with similar features.

5 Conclusions

To conclude, it is worth reiterating that the LBD contains great new data to study business dynamics and to guide our thinking about important macro questions. The paper by DHJM presents some very nice and thought-provoking findings and is certainly only the beginning of an exciting new research program. The finding, in particular, that the volatility trends of all firms do not coincide with the volatility trends of publicly-held firms that have been studied in previous papers certainly deserves attention, since it changes the basic stylized fact that the growing theoretical literature connecting business-level volatility with aggregate volatility must confront.

One interesting way to push this research agenda forward, especially in its relation to macroeconomics, is to bring more theory to the interpretation of data, since some important questions regarding the source of the decline in aggregate volatility are not possible to answer without it.

Endnote

1. The other parameters are set at annual values of $r = 0.05$, $\theta = 0.012$, $\mu = 0.5$, $w = 1$, $c_f = 0.5$, and $c_h = 0.5$. Details of the calculations and simulations are available upon request.

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Discussion

Diego Comin began the discussion by raising several points. He noted that it was entirely possible for time series and cross-sectional measures of firm volatility to behave very differently. While the cross-sectional measures of volatility capture the dispersion of the distribution of firm growth, the time-series measures of volatility get at the changes in a firm's position within this distribution. He mentioned that in work with Sunil Mulani, he had found that turnover had increased more in the COMPUSTAT sample. Using sales data rather than employment data, they furthermore found a decrease in the cross-sectional measure of volatility in the COMPUSTAT sample. Thomas Philippon remarked that similar trends vis-à-vis the convergence in cross-sectional volatility between private and publicly-traded firms had been observed in French data.

Comin noted that if the authors' conclusions are correct, they are particularly interesting because they help distinguish between different explanations that have been put forward regarding the upward trend in the volatility of public companies. In particular, he saw the authors' evidence as supporting Schumpeterian models in which firms that do a disproportionate amount of R&D, such as public firms, experience larger increases in volatility. On the other hand, he saw the authors' evidence as posing a challenge for models that stress financial frictions.

Comin emphasized the importance of controlling for compositional change by including firm fixed effects in the regressions. He noted that while the results could be driven by compositional change, in his own work on the COMPUSTAT sample, he had found that this was not the case. He noted that his results were also robust to the inclusion of age effects, size effects and to different weighting schemes, and said that he would like to see whether the results in the paper were robust to these effects as well.

Both Comin and Philippon noted that while the firms in the COMPUSTAT sample accounted for only about one-third of total U.S. employment, they accounted for a much larger fraction of value added in the economy. This implied that the weights were very different if firms were weighted by sales rather than employment. John Haltiwanger agreed that it was important to look at measures of activity other than employment. He noted that the LBD data set was particularly good for the employment variable, whereas investigating other measures would require significant additional work to construct these variables. Regarding entry and exit, Haltiwanger said that the results would not change significantly if sales weights were used instead of employment weights.

Daron Acemoglu cautioned against implicitly adopting a steady-state view of the economy when thinking about firm volatility. He noted that the entry of a large retail firm like Wal-mart in a particular local market typically induces a spike in hiring and firing activity, and this non steady-state phenomenon should affect the interpretation given to the empirical results. He also suggested that monotonic selection of less risky firms into public listing was not necessarily a good assumption. In response to an improvement in financial development, he argued that the most risky firms might seek and obtain a public listing since these firms have the biggest need for risk diversification. This would imply that the pool of listed firms would contain both old, low-risk firms and young, high-risk firms. Steven Davis responded that while the logic of Acemoglu's argument was correct, the quantitative force of this argument was not strong enough to explain the volatility convergence result.

Philippon said that he thought the take-away message from the paper was that economists need to think more about the decision of firms to go public. Two parameters he felt were particularly important in determining which firms go public are the amount of risk and the amount of asymmetric information. Firms should be more likely to go public the more risky they are and the less they are plagued by asymmetric information, other things equal. Philippon emphasized that the asymmetric information in IPOs was a very large phenomenon which led to a large amount of underpricing. In order to explain the large increase in the fraction of firms that go public, he felt that it was important to examine closely the role of improved financial intermediation, such as the rise of venture capital, in reducing asymmetric information problems. John

Haltiwanger agreed with Philippon's point and said that the authors were actively working on integrating the information in the LBD with venture capital data. He noted that with the dataset they had created, they could study the prehistory of firms that go public.

Andrew Levin urged the authors to think about the possible causal links between the trends they observe in firm level volatility and the Great Moderation in macroeconomic volatility since the mid-1980s. He noted that the causation could go either way and that it was even possible that there was no link. It seemed to him, however, that the authors were rather hesitant to draw any link between the Great Moderation and the trends in firm level volatility that they documented. Olivier Blanchard wondered whether the difference in volatility between public and private firms was primarily due to the larger size of public firms.

Responding to the discussants' comments, Haltiwanger noted that it was reassuring that there were now multiple datasets for the U.S. based on different sources from which consistent empirical patterns have emerged. He said that they had emphasized the retail sector in the paper since they were better able to ascertain the reasonableness of their results for this sector than for some other sectors. He however emphasized the pervasiveness of their findings across sectors. He noted that one potential explanation for the results was a shift in the economy towards larger national firms, but that many other explanations likely played a role.

Haltiwanger said that they were confident that the data showed a decline in entry and exit. He noted that in a large class of models with frictions, entry and exit played a very important role. He discussed work that he had done with Steven Davis and Jason Faberman showing that in the JOLTS data, the employment growth distribution has fat tails and that in light of this, entry and exit is particularly important.

Ron Jarmin rounded up the discussion by encouraging researchers to exploit the LBD dataset. He noted that research proposals could be submitted easily to the Census Bureau (via the Bureau's website) for access to the dataset.