

The Great Micro Moderation*

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November 18, 2017

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Abstract

This paper documents that individual income volatility in the United States has declined in an almost secular fashion since 1980—a phenomenon that we call the “Great Micro Moderation.” This finding contrasts with the conventional wisdom, based on studies using survey data, that income volatility—a simple measure of uncertainty—has increased substantially during the same period. The finding of declining volatility is consistent with a handful of recent papers that use administrative data. We substantially extend the existing empirical findings of declining volatility using data from both administrative and survey-based data sets. A key contribution of our paper is to link patterns of income volatility on the worker side to outcomes (and volatility) on the firm/employer side. With the information revealed by these linkages, we investigate several potential drivers of this trend to understand if declining volatility represents a broadly positive development—declining income risk and uncertainty—or a negative one, i.e., declining business dynamism.

JEL Codes: E24, J24, J31.

Keywords: Income inequality, income volatility, income instability.

*Special thanks to Pat Jonas, Kelly Salzmann, and Gerald Ray at the Social Security Administration for their help and support. The views expressed herein are those of the authors and do not represent those of the Social Security Administration and do not indicate concurrence by members of the research staff or the Board of Governors of the Federal Reserve System.

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1 Introduction

The rise in the dispersion of income *levels* across individuals—i.e., income inequality—is a widely accepted fact of the US economy.¹ However, whether the dispersion of income *changes* or income *growth*—what is known as income volatility or instability—has also increased is still the subject of considerable debate. Dispersion in growth rates of earnings may be informative about the degree of uncertainty or risk that workers face, and hence may have important policy implications (although not all volatility observed in the data is necessarily risk; see, e.g., [Low et al. \(2010\)](#); [Güvenen and Smith \(2014\)](#), and the references therein). Following the seminal work of [Gottschalk and Moffitt \(1994\)](#), and with few notable exceptions ([Sabelhaus and Song \(2009, 2010\)](#)), the broad conclusion of the literature is that income instability has risen over time. This increase in volatility is in contrast with the evolution of most macroeconomic and microeconomic time series, which have shown a large decline in volatility (the so called “Great Moderation”).

In this paper, we revisit this important issue by offering two main contributions to the debate: (a) we use much better data than those used in the existing literature, and (b) we link trends in wage instability with trends in firm outcomes volatility.

Our main data source is a large dataset drawn from the Master Earnings file of the Social Security Administration for the universe of US employees between 1978 and 2013. Earnings in this dataset are recorded at the individual level and are not subject to bottom or top coding. Using administrative records gives us several advantages relative to existing studies. First, our dataset follows any individual that has ever issued a Social Security number in the United States, allowing us to study the evolution of earnings growth dispersion for a much larger sample of individuals and within narrowly defined population groups. Second, since the earnings information that we use comes from administrative records, problems such as sample attrition or measurement error, which are pervasive in survey data, are almost nonexistent in our dataset. Third, ours is a firm-worker matched data set which allows us to study how individual-level outcomes relate to firm-level outcomes.

Our second contribution consists of jointly studying the trends on wage instability and firm-level outcomes volatility. There is a growing literature on the importance of firm effects for explaining the rise in earnings inequality ([Card et al. \(2013\)](#); [Barth et al.](#)

¹See, e.g., [Katz and Autor \(1999\)](#); [Acemoglu and Autor \(2011\)](#), for recent surveys of this evidence.

(2014); Song et al. (2016)). We study instead the link between changes in firm volatility and changes in earnings instability.

We document four main findings. First, in contrast with the seminal work of Gottschalk and Moffitt (1994) and others, we find that earnings growth volatility has decreased substantially since the 1980s: the 90th-to-10th percentiles spread of the distribution of one-year earnings changes declines by 40 log points between 1980 and 2013. We find a similar decline in earnings growth dispersion if we look at narrow population groups defined by gender, age, or birth cohort; if we consider five-year changes in earnings (a measure of permanent earnings changes); and when using different definitions of dispersion. Moreover, using a smaller sample—also drawn from the SSA records—we find that the drop in earnings growth dispersion that we observe from the 1980s onward is in fact part of a longer trend that started in the early 1960s.

Second, the decline in income instability mirrors a large decline in the dispersion of employment and average wage growth at the firm-level. Hence, there is evidence of a “great moderation” in micro data on both worker and firm outcomes. In particular, between 1980 and 2013, we find a 20 points decline in the dispersion of one-year employment growth changes and a 15 log points decline in the dispersion of one-year average wage changes. As in the case of individual earnings, the drop in dispersion is also seen if we stratify the firm sample by observable characteristics, such as industry, size, or firm age. We document similar patterns when we account for the entry and exit of firms and when using five-year changes in employment and average wages.

Third, we find that most of the decline in earnings volatility is explained by a decrease in the proportion of individuals switching jobs. In fact, a simple decomposition shows that, although the level of dispersion of earnings growth is larger for individuals that change employer in a given year relative to those that stayed in the same firm, these levels have remained relatively stable over the last 30 years. However, it is the share of individuals that stay with the same firm what has increased over time, pushing down the dispersion across the population.

Finally, we put the two main findings together and show that the drop in business growth volatility is an important factor behind the decline of earnings instability. Our estimates suggest that, conditional on firm and sectoral characteristics, a 10 percent decrease in the dispersion of firms employment growth within a sector (one-digit SIC) is associated to a 4.2 percent decrease of the dispersion of the growth rate of earnings of

the individuals that work in that sector. This holds true when we control for time and sector fixed effects, firms characteristics (such as age and size), and characteristics of the workforce within sectors (such as gender, age, education, etc.).

This paper is related to two large and active literatures that go back several decades. The first literature is the one mentioned above about income volatility. The seminal papers that launched this literature are [Gottschalk and Moffitt \(1994\)](#) and [Moffitt and Gottschalk \(1995\)](#). The authors consider an income process that is the sum of a transitory component and a permanent component. They interpret transitory changes in income as measuring the extent of income volatility (or instability). Using PSID, they find that the variance of the transitory component has increased substantially, particularly in the 1970s and 1980s.

Other papers have painted a more nuanced picture. For example, [Shin and Solon \(2011\)](#) cast some doubts on the identification strategy of [Gottschalk and Moffitt \(2009\)](#), and find (again using PSID data) that men’s earnings growth volatility surged during the 1970’s but did not show a clear upward trend in later years. [Ziliak et al. \(2011\)](#) findings, based on matched data from the CPS March supplements, are similar: earnings growth volatility among men increased by about 15% since the 1970 to mid 1980s and stabilized after that period. Earnings growth dispersion for women fell substantially since the late 1970s. With the few exceptions noted below, all the work in this literature has used survey-based datasets and broadly confirmed Gottschalk and Moffitt’s finding of rising earnings and income volatility.²

A few recent papers have turned to administrative data from the SSA and found either a flat pattern in income volatility ([Congressional Budget Office \(2007\)](#)) or a declining trend ([Sabelhaus and Song \(2009, 2010\)](#)). Our paper is more closely related to these recent papers that cast doubt on rising volatility. Relative to these papers, we study a broader set of statistics and we examine how the declining volatility is related to the changes observed at the firm and industry levels.

The second literature examines trends in various labor market outcomes—job creation and destruction rates, gross/net worker flows, employment to unemployment transition rates, among others—and finds that most measures of volatility have declined since the

²The vast majority of these studies have used panel data from the Panel Study of Income Dynamics (PSID), although a few more recent papers have used 1-year income changes that can be constructed from the Current Population Survey (CPS). See [Dynan et al. \(2007\)](#) for a review of this literature, including the data source, sample selection, and the findings.

1980s ([Davis et al. \(2007\)](#); [Shimer \(2007\)](#); [Davis et al. \(2010a\)](#) and [Decker et al. \(2016\)](#)). The empirical findings indicating rising income volatility has always seemed somewhat puzzling in light of this related evidence (see [Davis and Kahn \(2008\)](#)). However, because of the survey-based nature of the data sets used in this literature, most researchers were unable to analyze businesses volatility together with trends in individual incomes. Our analysis combines data on individual earnings with data of the firms these individuals work for. This allows to link these two disparate literatures and obtain a better understanding of the drivers of the changes that have been happening in the US labor market over the last 40 years.

The rest of the paper proceeds as follows. In Section 2 we present the data, while Section 3 documents the main facts on earnings and employment volatility. In Section 4 we discuss why previous papers based on survey data show different findings, while in Section 5 we investigate the importance of composition effects. Section 6 links measures of worker volatility with measures of firm volatility. Section 7 concludes.

1.1 SSA Relevance

The volatility of individual earnings is a key input for the projections and analyses conducted by the Social Security Administration. In fact, the earliest paper on the topic that used administrative data was a report prepared by the [Congressional Budget Office \(2007\)](#) (CBO) in response to a request by the US Senate’s Joint Economic Committee, precisely because this information was considered central to the analyses and projections about the US Social Security system. The CBO letter accompanying its analysis succinctly explained the purpose of the report: “...[T]he CBO is analyzing the extent to which workers’ earnings and family incomes vary from year to year and whether that variability has changed over the past 20 years. CBO’s analysis of lifetime earnings patterns is a key input into its projections for Social Security and Medicare, because revenue outlays are directly tied to individual workers’ earnings through tax and benefit formulas.”

In addition to this direct effect on Social Security’s revenues and pension obligations, earnings variability also directly affects how well or how poorly workers are prepared for retirement. For example, large falls in workers’ earnings (especially if they persist over several years) can cause them to liquidate their assets to provide for consumption, leaving less resources for retirement while at the same time, higher variability in earnings

can lead workers to accumulate a larger buffer stock of wealth which can then provide for income during retirement. Therefore, knowing the extent to which earnings variability has changed over time would inform researchers both inside and outside of the SSA and help provide more accurate projections for the future.

With this motivation, our paper revisits this important question, and extends the analysis using 10 years of additional data, a period that covers the Great Recession and its aftermath, and with a decade more information on the the aging of baby boom cohorts. Another key contribution of our paper is to study the link between the workers and their employees and provide a detailed analysis to understand the extent to which the changes in earnings variability for workers was linked to changes we observed on the employer side. In particular, a parallel literature in macroeconomics has documented a decline in volatility on the firm side (e.g., [Davis et al. \(2007\)](#))—in the variability of firm employment growth, worker movements across firms, among others—and we examine whether the two trends are linked. We also examine in more detail than previous studies how the earnings variability trends differed across industries, birth of year cohorts, employers of different sizes, among others. Because employers are another source for workers of pension income as well as health and disability insurance that complements the SSA’s programs, a better understanding of how firms contribute to the changes in earnings variability helps with more accurate projections, thus furthering the SSA’s policy objectives.

2 Data

The main data source for this paper is the Master Earnings File (MEF) of the U.S. Social Security Administration (SSA). The MEF contains earnings records for every individual who has ever been issued a U.S. Social Security Number. Along with basic demographics (such as sex, date of birth, etc.), the MEF contains labor earnings information for every year from 1978 to 2013. Earnings data in the MEF are based on Box 1 of Form W-2, which is sent directly by employers to the SSA. Data from Box 1 are uncapped and include wages and salaries, bonuses, tips, exercised stock options, the dollar value of vested restricted stock units and other sources of income deemed as remuneration for labor services by the U.S. Internal Revenue Service. We convert earnings data to 2012 real values using the personal consumption expenditures (PCE) deflator. Because earnings data are based on the W-2 form, the dataset includes one record for each individual, for

each firm they worked in, for each year.

This earnings information, plus the unique employer identification number (EIN) for each W-2 record registered in the MEF allows us to use worker-side information to construct firm-level variables. Workers who hold multiple jobs in a given calendar year are linked with the firm that provides the highest earnings for that year. The resulting matched employer-employee is a very rich dataset containing information for each individual on the total earnings, gender, age, location, and characteristics of the firms where they work (such as sector, size, average wage, average tenure, employment growth, etc). On the firm side, the dataset contains information on the firms' characteristics (sector, size, maturity, etc.) and on the composition of the employees of the firm in terms of gender, age, and tenure.

Sample Selection

Our baseline sample of individuals and firms is constructed as follows. First, a worker must be between 25 and 64 years old (both ends included). Second, the worker must have earnings above a time-varying threshold equal to the amount one would earn by working full time for a quarter of the year (13 weeks at 40 hours per week) at half of the federal minimum wage.³ This condition is standard in the income dynamics literature and ensures that we select individuals with reasonably strong labor market attachment (see, e.g., [Abowd and Card \(1989\)](#) and [Meghir and Pistaferri \(2004\)](#) or [Guvenen et al. \(2015\)](#) and [Guvenen et al. \(2014\)](#) using the same dataset as we use here). We additionally drop individuals working in Education Services (SIC between 8022 and 8299) or in the Public Sector (SIC above 9000). Consequently, our firm-level data set consists of all the EINs that hire at least one individual satisfying the age, income criteria, and industry criteria.

Growth measures for workers and firms

Our measure of earnings at the individual level, ω_{it} , is the total amount of income that an individual i obtained during the entire year t across all the firms that she worked for ($\omega_{it} = \sum_j \omega_{ijt}$), where j is a subscript for firm j . Nominal wages are deflated using the Personal Consumer Expenditures index (PCE). At the firm level, we identify a firm by

³Around \$1,812 in 2012 dollars.

its EIN and construct total employment, n_{jt} , as the sum of all individuals that worked in a EIN in a particular year (note that the same person can have more than one job). Then, we construct the average wage of a firm j in period t as the firm’s wage bill divided by total employment.

For each of these variables, we construct moments of the cross-sectional distribution of growth rates between periods t and $t + k$. For most of the calculations reported below the growth rate measure is the log-difference between periods t and k , i.e., $\Delta x_t^k = \log x_{t+k} - \log x_t$ (for $x = \{\omega, n\}$). Since workers, and especially firms, experience entry and exit, we also measure growth using the arc-percentage change between years t and $t + k$. The arc-percentage change, defined as $dx_t^k = 2(x_{t+k} - x_t) / (x_{t+k} + x_t)$, has been popularized in the firm dynamics literature by [Davis and Haltiwanger \(1992\)](#) and has the advantage that, while similar to a percentage change measure, it is defined even when x_{t+k} or x_t are zero.

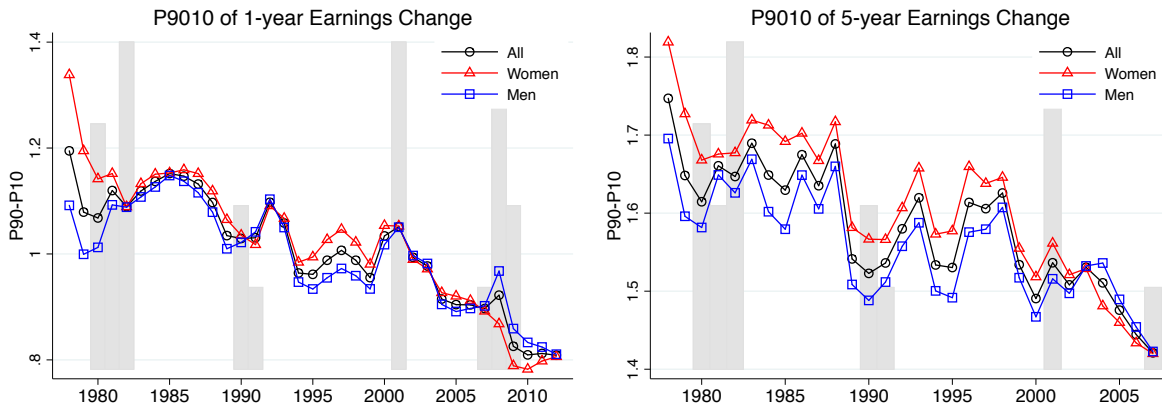
3 The Decline in Microeconomic Dispersion

3.1 Workers

In this section we analyze the evolution of the dispersion in individuals’ earnings growth rate. For most of the paper, our preferred measure of earnings growth volatility is the 90th-to-10th percentiles spread ($P9010$). Relative to other measures of dispersion, the $P9010$ has the advantage of being less influenced by outliers. Moreover, it can be easily decomposed into right tail dispersion (the 90th-to-50th percentiles spread, or $P9050$) and left tail dispersion (the 50th-to-10th percentiles spread, or $P5010$), since by definition: $P9010 = P9050 + P5010$.

The left panel of [Figure 1](#) shows the cross-sectional dispersion of the one-year growth rate of earnings (for the whole sample, and separately for men and women). The first striking finding is that, in contrast to most of the previous literature (e.g. [Gottschalk and Moffitt \(1994\)](#), [Gottschalk and Moffitt \(2009\)](#), or [Ziliak et al. \(2011\)](#)), we find a clear decreasing trend in overall dispersion. In particular, the $P9010$ declines by one third from 1.2 to 0.8 over a thirty-four years period. Second, the decline is similar for men and women, although slightly more pronounced among women. Third, around the trend there is cyclical pattern with dispersion rising towards the end of recessions. Fourth,

FIGURE 1 – DISPERSION OF EARNINGS GROWTH



Note: The left panel of figure 1 shows the time series of 90th-to-10th percentiles spread of the cross-sectional distribution of one-year log change of real earnings for the full sample and separating women and men. Similarly, the right panel reports the 90th-to-10th percentiles spread of the cross sectional distribution of five-years log change of real earnings. Shaded areas represent NBER recession years.

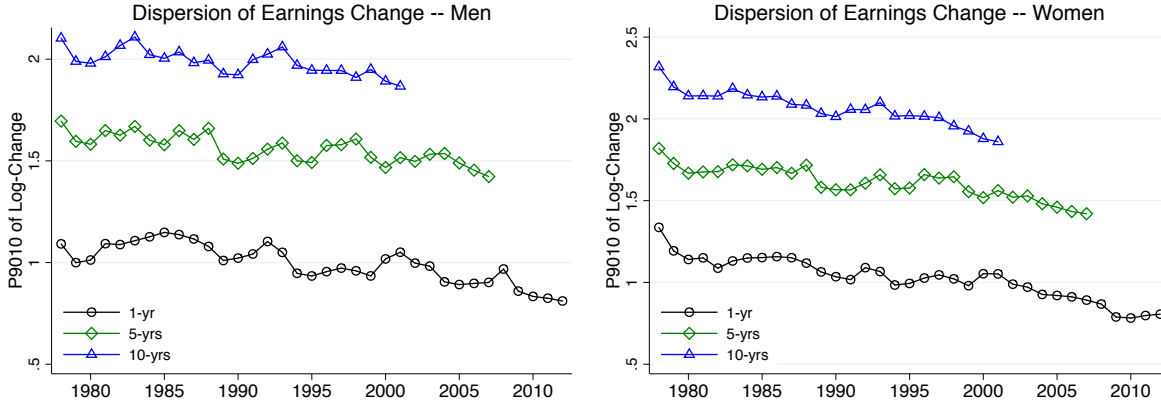
the dispersion of more permanent changes has also decreased substantially —by about one quarter —as shown in the right panel of Figure 1, which plots the cross sectional dispersion of five-year earnings growth rates.

One important question is whether the decline in volatility signals worsening upside potential or improving downside risk. Some of the decline in volatility may have come from large wage hikes becoming less frequent; or from large wage cuts becoming less likely. In Figure 3 we show that, in fact, the decline in dispersion occurs both at the right and the left tail of the distribution. Of note is that during recessions, and especially during the two more recent ones, the frequency of wage hikes decreases while the frequency of wage cuts rises.

3.1.1 Declining *Volatility* vs Rising *Inequality*: Are They Compatible?

There is a vast literature documenting the rise in earnings inequality in the United States (see Katz and Autor (1999); Acemoglu and Autor (2011), for recent surveys of this evidence). In this paper we document a decrease in wage volatility (i.e., a decrease in the dispersion of earnings growth rates). Are the two phenomena compatible? To see whether this is the case, we now move to measuring dispersion with variances rather than percentile differences. The advantage is that the variance of the growth rate is easily decomposable. Consider the following decomposition of the variance of the growth rate of earnings between periods t and $t + 1$:

FIGURE 2 – DISPERSION OF EARNINGS GROWTH



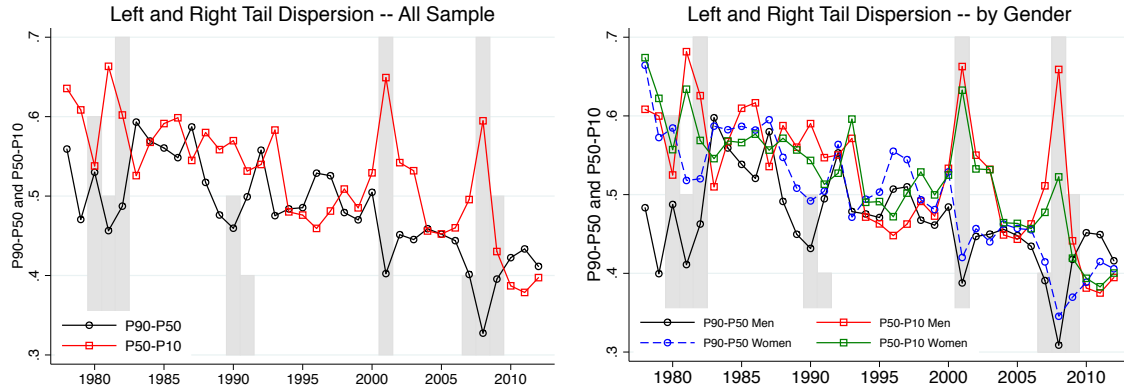
Note: The left panel of figure 2 shows the time series of 90th-to-10th percentiles spread of the cross-sectional distribution of one-year log change of real earnings for the full sample and separating women and men. Similarly, the right panel reports the 90th-to-10th percentiles spread of the cross sectional distribution of five-years log change of real earnings. Shaded areas represent NBER recession years.

$$\text{Var}(\log \omega_{i,t+1} - \log \omega_{i,t}) = \text{Var}(\log \omega_{i,t+1}) + \text{Var}(\log \omega_{i,t}) - 2 \times \text{Cov}(\log \omega_{i,t+1}, \log \omega_{i,t}). \quad (1)$$

If the variance of earnings *growth* is decreasing (left side of equation (1)) while the variance of earnings *levels* is increasing (first and second term of the right side of equation 1), it must be the case that the covariance of earnings between periods $t + 1$ and t is increasing over time (last term of equation 1), so that it more than compensates the increase of the dispersion of earnings *levels*. In other words, earnings must have become more persistent over time. Figure 4 shows that this is the case.

In the figure, the black line with circles shows the cross sectional variance of workers earnings growth, which replicates the same declining pattern observed using the 90th-to-10th percentiles difference; the blue-squared is the variance of log earnings, which shows the well documented increase in earnings inequality; and the red-triangles line is the covariance of log earnings between two consecutive periods, which shows an increasing pattern. Such steady increase in the covariance more than compensates the rise in income inequality, driving the earnings growth volatility down. To have a clearer picture about the patterns of each time series, the right panel of figure 4 shows the same measures of variance and covariance, now rescaled to their corresponding values in 1980. This evidence casts doubt on any mechanism that relies on a simple increase in earnings

FIGURE 3 – LEFT AND RIGHT TAIL DISPERSION OF ONE-YEAR EARNINGS GROWTH



Note: The left panel of figure 3 shows the time series of 90th-to-50th and 50th-to-10th percentiles spread of the cross-sectional distribution of one-year log change of real earnings for the full sample. The right panel shows similar statistics separating men and women. Shaded areas represent NBER recession years.

shocks dispersion as a main explanation of the rise in income inequality.⁴

Does this evidence matter for any practical reason? The covariance between earnings at two dates is, effectively, a measure of how persistent earnings are. A finding that the covariance has been increasing means that earnings have become more persistent over time. This has important implications for wage mobility. It suggests that mobility has been declining over time, a version of the “Great Gatsby” hypothesis that is typically observed at the cross-country level (Krueger (2012)), where countries with higher levels of inequality have less mobility over time and across generations. Another implication is for the debate on whether the increase in inequality that we see in the data is structural or temporary. The evidence seems to dispel the idea that a fraction of the rise in inequality is transitory, and points to more permanent or structural factors, such as skill-biased technical change, increasing segregation of the labor market from outsourcing, etc.

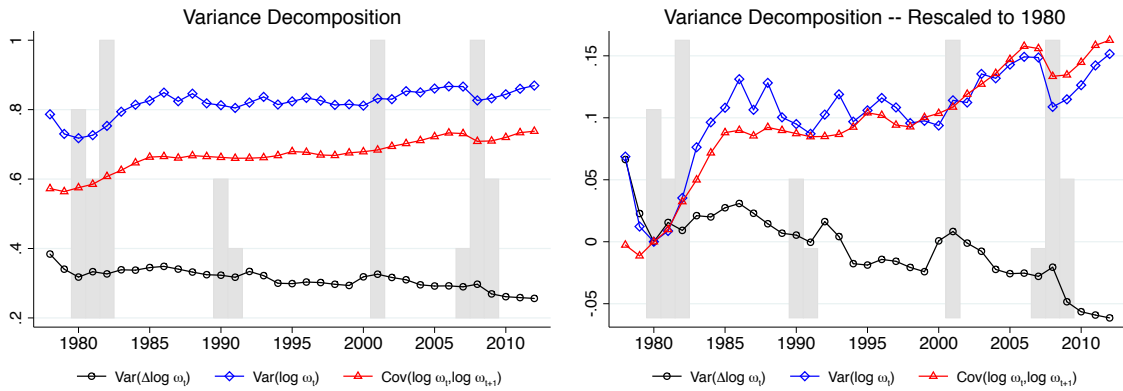
3.1.2 Worker heterogeneity by age

One possible explanation for the decline of earnings growth volatility is the aging of the US workforce, which median age has increased by 6 years since 1978.⁵ To study if this is the case, we separate our sample into four different age groups (25-34, 35-44, 45-54 and 55-64) and we calculate the dispersion of earnings growth within each group. The

⁴See for instance Heathcote et al. (2010) or Hubmer et al. (2016).

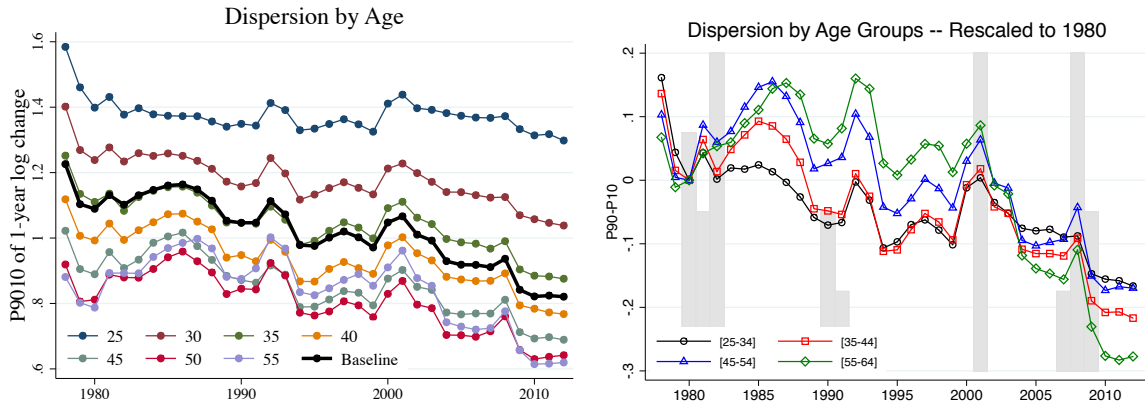
⁵The median age of the working age population remained stable between 1978 and 1989 and increased significantly afterwards.

FIGURE 4 – DISPERSION OF EARNINGS LEVELS AND GROWTH



Note: The left panel of figure 4 shows the time series of the cross sectional variance of one-year log change of real earnings, the cross sectional variance of the log of real earnings, and the covariance of the log of real earnings between two consecutive periods. The right panel shows the same statistics relative to their values in 1980. Shaded areas represent NBER recession years.

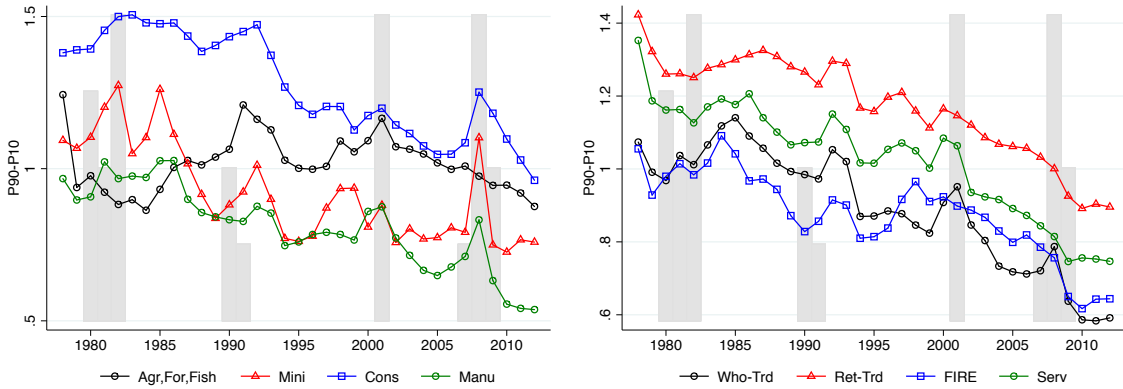
FIGURE 5 – DISPERSION OF EARNINGS GROWTH BY AGE GROUPS



Note: The left panel of figure 5 shows the time series of the 90th-to-10th percentiles spread of the cross sectional distribution of one-year log change of real earnings by age groups. The right panel shows the same statistics by wider age groups and relative to their values in 1980. Shaded areas represent NBER recession years.

left plot of Figure 5 shows two important facts. First, the dispersion of earnings growth has declined by about one third for all age groups, similar to the change observed in the whole population (see figure 1). This can be seen more clear in the right panel of figure 5 where we rescale the dispersion of each age group to its value in 1980. So the story appears to be primarily a within age-group decline in wage volatility. Second, dispersion is in fact not monotonically decreasing in age—the youngest 25-34 year old workers have the highest dispersion, while the oldest 55-64 group has a mid-level of variance, with the late-middle aged (45-54) workers having the lowest variance.

FIGURE 6 – DISPERSION OF EARNINGS GROWTH BY INDUSTRY



Note: Figure 6 shows the time series of the 90th-to-10th percentiles spread of the cross sectional distribution of one-year log change of real earnings for different industries at 1-digit SIC. Shaded areas represent NBER recession years.

3.1.3 Worker heterogeneity by industry

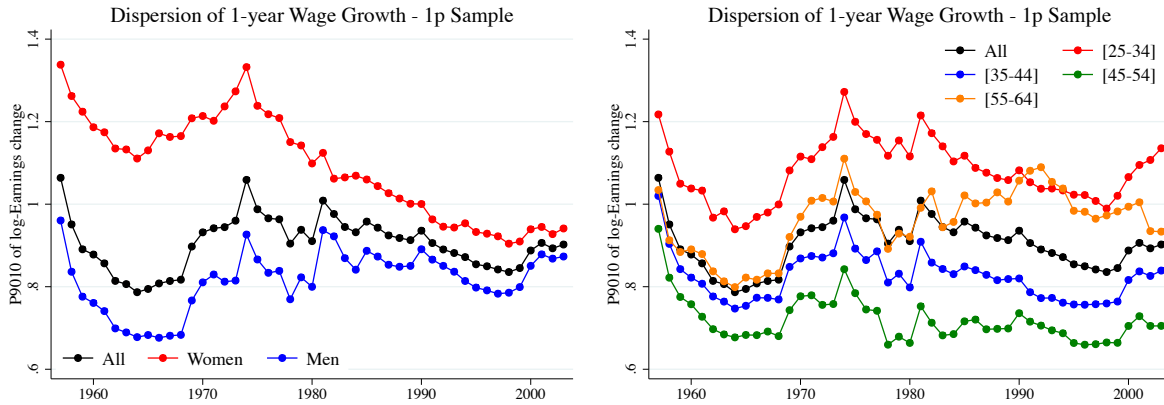
A different explanation could lie on the the large sectorial shifts observed in the US economy that has gradually moved from manufacturing to services. If workers are moving toward less volatile industries, then, it would be natural to see a decline in earnings volatility. To see if this is the case, we calculate the dispersion of earnings growth within 1-digit SIC groups. Figure 6 shows that the dispersion within each industry has declined substantially, and almost at the same rate for in each sector: with the exception of Agriculture, Forestry, and Fishing, dispersion of earnings growth declined between 40 and 50 log points for each of the sectors. This indicates that a simple sectoral shift cannot account for the large decline in earnings volatility. Moreover, to the extent that earnings volatility within Manufacturing is lower than earnings volatility within Services, the decrease of employment share accounted for by manufacturing firms cuts right in the opposite direction, pushing the overall dispersion of earnings growth up instead of down.

3.1.4 Worker heterogeneity by income

Next, we look at the dispersion of earnings growth conditional on the level of recent earnings. Here we focus on individuals with more than three years of earnings observations and define “recent earnings” as the average value of each individual’s log-earnings between periods $t - 1$ and $t - 5$ (for a maximum of five years).⁶ We then calculate the dis-

⁶By construction, this measure of recent earnings is skewed towards individuals with high labor attachment as we restrict our sampler to workers with at least three observations of annual earnings in a

FIGURE 7 – EARNINGS VARIABILITY IN THE LONGER SAMPLE: 1957 TO 204



Note: The data are from the 1% CHWS sample covering workers employed in the commerce and industry sectors.

persion of earnings growth between t and $t + 1$ within each percentile of the distribution of recent earnings. The left panel of figure 8 shows the $P9010$ for selected years.

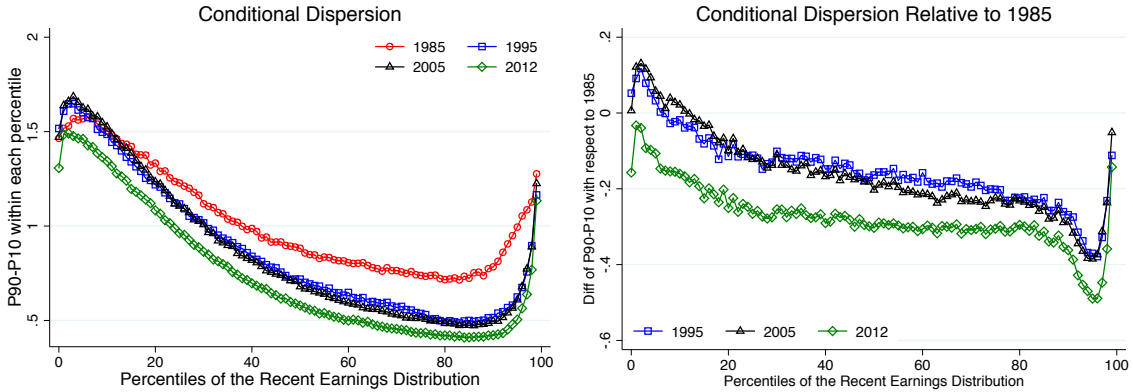
The first thing to notice is that the dispersion at the extremes of the earnings distribution is larger than in the middle. Second, comparing the distribution for different years, we find that dispersion of earnings growth has declined almost for all income levels, but especially among individuals in the upper half of the distribution. For instance, in 1985 the dispersion of the growth rate of earnings among workers at the 50th percentile of the recent earnings distribution was 0.88, while in 2012 it was 0.57, a decline of 30 log points. However, for individuals at the 95th percentile of the earnings level distribution the decline was 50 log points during the same period.

To better appreciate the large differences in the decrease of dispersion, the left panel of figure 8 shows the dispersion of earnings growth within each percentile relative to its value in 1985. Here the declining pattern is quite evident as we move from the left to the right of the plot. In the appendix, the figure A.7 shows similar patterns for long-term income changes and accounting for labor market entry and exit.

After establish that the dispersion of earnings growth has declined across almost almost all income *levels* , one can ask which part of the distribution of earnings *growth* is driving this drop. This is important because it gives information about the nature of risk that workers face at different earnings levels: conditional on reaching a certain level of earnings, have the chances of getting a positive income shock decreased? Have the

five-year span. However, results do not change substantially if we include in our calculations individuals with fewer observations.

FIGURE 8 – DISPERSION OF EARNINGS GROWTH CONDITIONAL OF RECENT EARNINGS



Note: The left panel of figure 8 shows the 90th-to-10th percentile differential of the cross sectional distribution of the one-year log change of real earnings conditional on the distribution of recent earnings. For each individual, recent earnings in period t are defined as the average of log-real earnings between periods $t - 1$ and $t - 5$. We drop observations of individuals whose recent earnings were calculated with less than three earnings observations. The right panel shows the same statistics relative to the level in 1985.

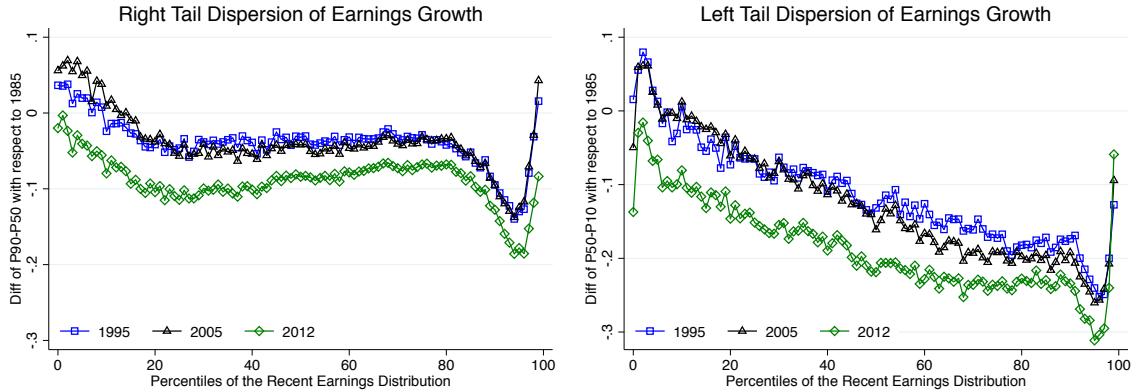
chances of getting a negative income shock decreased as well? If the former is true, then the decline of income growth instability has come with the consequence that workers now find more difficult to move up in the earnings distribution. However, if the latter is a more accurate description of the facts, then a drop in income instability is even more benign, as the probability of experiencing an income drop has declined as well.

To address these questions, the right panel of figure 9 shows the 90th-to-50th percentile spread of the earnings growth distribution, conditional on the level of earnings, relative to its value in 1985. The decline is quite marked, especially after 2000 and for individuals in the upper deciles of the income distribution, suggesting that the chances of experiencing positive earnings growth conditional on income have declined in recent years. The dispersion below the median, however, seems to have declined much more dramatically, particularly for individuals in the upper half of the earnings distribution, as it is shown in the right panel of figure 9. This indicates that the majority of the drop in income volatility is driven by a decline of the left tail of the earnings growth distribution.

3.2 Firms

Any analysis of the evolution of individual's wage growth dispersion is incomplete without a study of the firms that hire those individuals. Historically, there has been some debate

FIGURE 9 – LEFT AND RIGHT TAIL DISPERSION CONDITIONAL ON RECENT EARNINGS



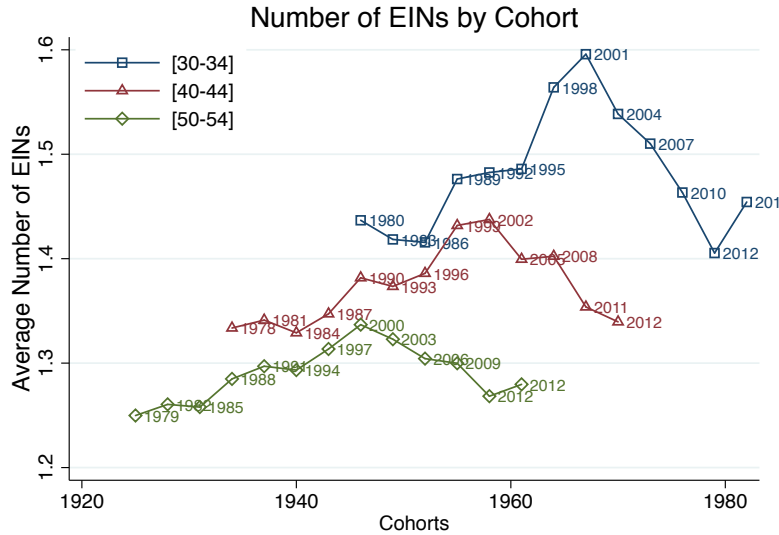
Note: The left panel of figure 9 shows the 90th-to-50th percentile differential of the cross sectional distribution of the one-year log change of real earnings, conditional on the distribution of recent earnings. Similarly, the right panel shows the 50th-to-10th percentiles spread. For each individual, recent earnings in period t are defined as the average of log-real earnings between periods $t - 1$ and $t - 5$. We drop observations of individuals whose recent earnings were calculated with less than three earnings observations. Statistics are plotted relative to their values in 1985.

over the evolution of firm-level volatility. For instance, [Comin and Philippon \(2005\)](#) show, using Compustat data (and hence publicly traded firms), that the volatility of employment and sales growth had increased over time; in contrast, [Davis et al. \(2010b\)](#) use establishment-level data from the Longitudinal Business Dataset data (which include both public and privately owned firms) and find the opposite, while [Bloom \(2014\)](#) surveys a range of papers and datasets to report strongly counter-cyclical increases in dispersion but less consensus on long-run trends. Since our dataset includes the universe of firms in the US economy, we can revisit these important issues, look at the dispersion of employment growth and average wage growth, and importantly, assess how the dispersion of outcomes at the firm-level impacts the dispersion of earnings growth at the workers level.

The information that we use here is aggregated at the firm-level (instead of at the establishment-level as in the Longitudinal Business Dataset). Since most of the wage and employment decisions are centralized, a firm-level dataset is more suitable to study the evolution of the growth rate of employment and wages.⁷ In parallel to what we have documented in the previous sections for worker outcomes, our main finding here is a sharp decline in the dispersion of employment growth and mean wage growth at the firm level. Figure 11 shows the time series of the 90th-to-10th percentiles differential for the one-year growth rate (left panel) and for the five-years growth rate (right panel) of

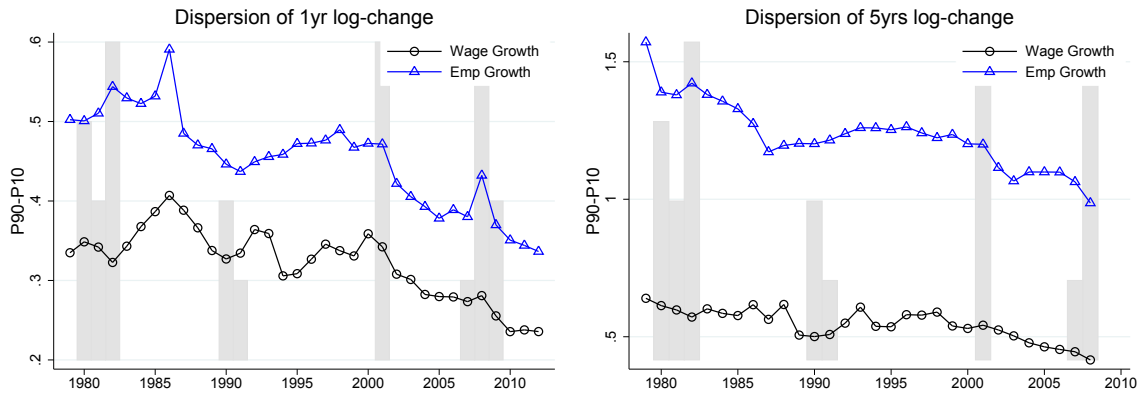
⁷See [Song et al. \(2016\)](#) for further discussion.

FIGURE 10 – EINS BY COHORT



Note: The figure shows the number of EINS by cohort of workers.

FIGURE 11 – DISPERSION OF THE GROWTH RATE OF EMPLOYMENT AND MEAN WAGE



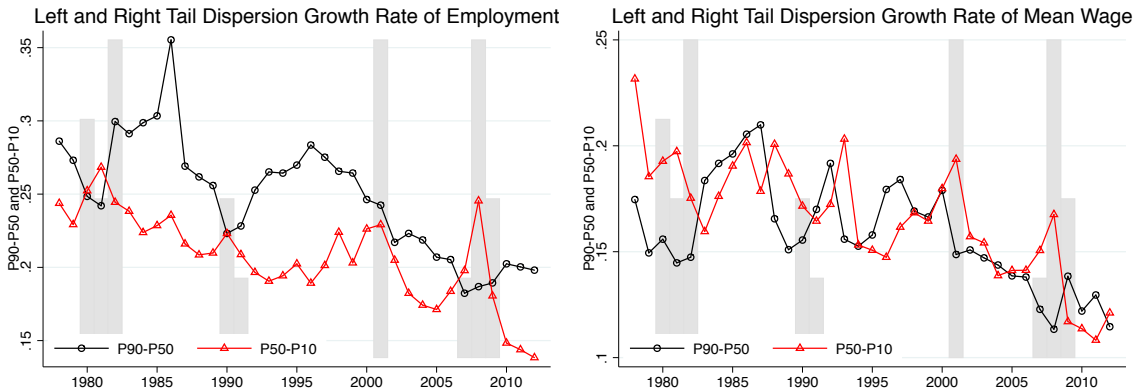
Note: The left panel of figure 11 shows the 90th-to-10th percentile differential of the cross sectional distribution of one-year log change of employment growth and one-year log change of average real wages at the firm-level. The right panel shows the same measures for five-year log changes. Shaded areas represent NBER recession years.

employment and mean wages.

The decline is quite significant for each variable: the $P9010$ of employment growth declines 20 log points between 1979 to 2013, while the decline is about 15 log-points for mean wage growth dispersion (due mostly to aggregation, this is roughly half of the total decline in the dispersion of individuals earnings reported in section 3.1).⁸ As in the case

⁸As said above, the empirical literature on firm dynamics has discussed extensively whether firm-level volatility has increased over time. The evidence presented by Davis et al. (2010b) showed a

FIGURE 12 – RIGHT AND LEFT TAIL DISPERSION OF GROWTH RATES OF EMPLOYMENT AND MEAN WAGES



Note: Figure 12 shows the 90th-to-50th and 50th-to-10th percentiles spread of the cross sectional distribution of one-year log employment change (right panel) and log of real mean wage change (right panel). Shaded areas represent NBER recession years.

of workers, the decline in dispersion is observed at both ends of the distribution as it is shown in figure 12. Taking into account entry and exit of firms, as we do in figures A.8 and A.9, does not change substantially our results.

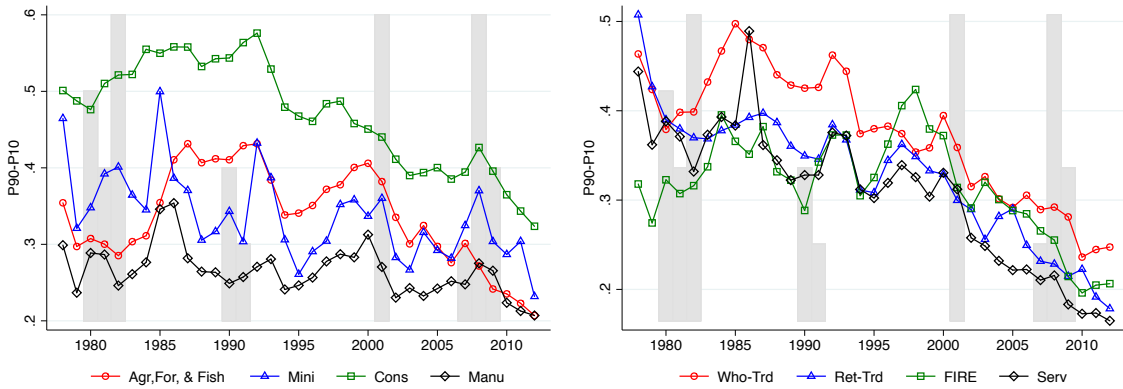
3.2.1 Firm heterogeneity

In this section we investigate whether the declining micro volatility at the firm level differs by key firm characteristics such as sector, size, or firm age. First, we find that dispersion of employment growth and mean wage growth has not only declined overall, but also, within more narrowly defined industry sector as it is shown in figure 13, for mean wage growth, and 14 for employment growth. This evidence indicates that the decline of the cross sectional dispersion is not explained by a simple shift in the industry composition of the US economy from high to low dispersion sectors.

Second, it is well know that smaller (and typically younger) firms show larger growth rate dispersion than larger (and typically older) firms. We find that despite these differences, the decline of dispersion in employment and wage growth is very similar for firms of different sizes, albeit somewhat greater for smaller firms. To see this, figure 15 shows the dispersion of employment and wage growth for four different firm-size categories.

clear distinction between private and publicly traded firms as the later showed an increasing pattern of dispersion (see Campbell (2001)). However, as we shown in the appendix Figure A.11, the post-2000 decline in the dispersion of firm-level outcomes is also present among publicly traded firms.

FIGURE 13 – DISPERSION OF GROWTH RATES OF MEAN WAGE GROWTH BY 1-DIGIT SIC



Note: Figure 13 shows the 90th-to-10th percentile differential for the cross sectional distribution the one-year log change real mean wage by one-digit SIC. Shaded areas represent NBER recession years.

For both wages and employment growth, we find a consistent declining pattern which is especially strong for firms between 5 and 49 employees: in the case of employment, the level of dispersion declines by about 15 log-points, while for wages, the decline is 10 log-points.

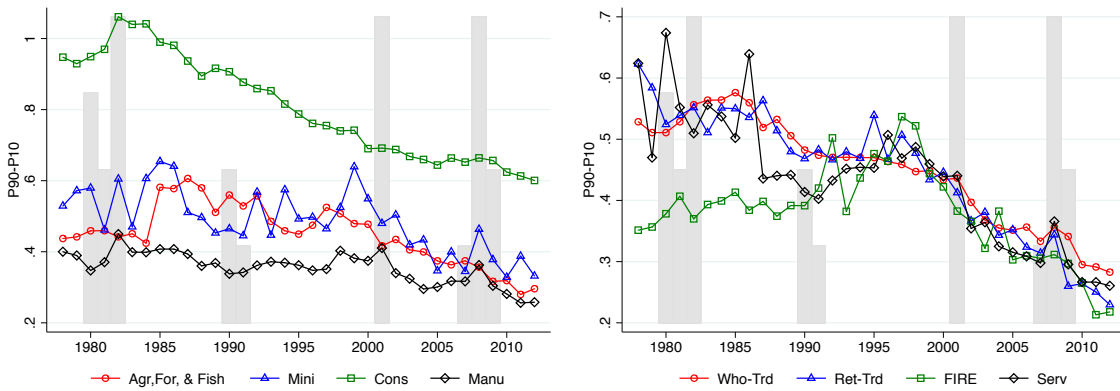
Since the share of young firms has been declining over time, especially after 2000 (see Decker et al. (2016)), we next investigate trends of employment and wage growth dispersion for firms of different maturity. We define the entry year of a firm as the year in which the EIN is first observed (i.e., the firm has one employee or more for the first time). In that year, we set the firm’s age to 0 and we then increase the age of the firm by 1 for every consecutive year in which the firm has at least one employee. Here, we do not consider firms whose age cannot be determined (firms present at the beginning of our sample)⁹ Figure 16 shows that the dispersion of the growth rate of employment (left panel) and wages (right panel) declines in tandem across all firm age categories.

3.2.2 Jobs and Workers Reallocation

The decline in the frequency of large employment changes documented above may nevertheless be consistent with continuing job reallocation activity. For example, a firm may be firing and hiring the same number of workers, resulting in zero net employment growth. If firms find it increasingly easier to replace departing workers due to a decline in

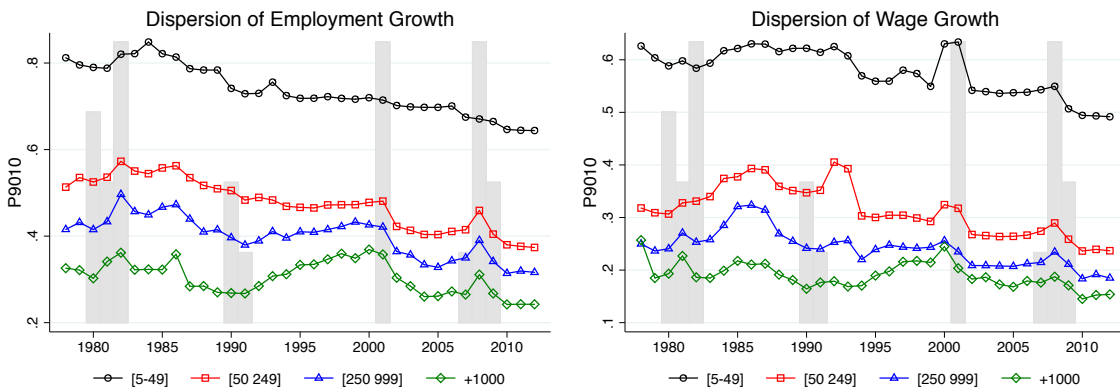
⁹Dispersion is also falling for this group of firms also, but most probably because all these firms are mature.

FIGURE 14 – DISPERSION OF GROWTH RATES OF EMPLOYMENT GROWTH BY 1-DIGIT SIC



Note: Figure 14 shows the 90th-to-10th percentile differential for the cross sectional distribution the one-year log employment change by one-digit SIC. Shaded areas represent NBER recession years.

FIGURE 15 – DISPERSION OF GROWTH RATES OF EMPLOYMENT AND MEAN WAGES BY FIRM'S SIZE

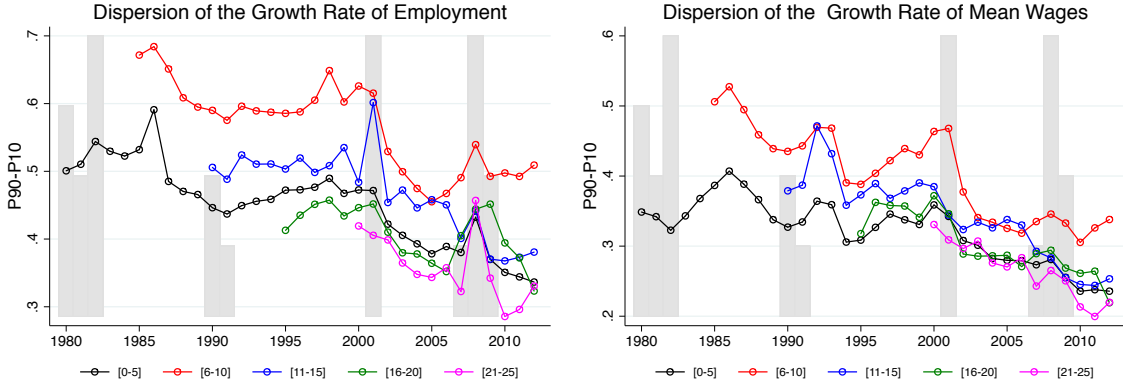


Note: Figure 15 shows the 90th-to-10th percentile differential for the cross sectional distribution of one-year log employment change (left panel) and the cross sectional distribution of one-year log real mean wage change (right panel) for four different size groups. Shaded areas represent NBER recession years.

recruiting frictions, large employment changes may become less frequent despite a great deal of job churning. A key advantage of our data set is that it allows us to distinguish between reallocation of jobs across firms and reallocation of workers. The first define a change in the number of labor positions available to workers, while the second refers to changes in the number of workers.

To construct a measures of job reallocation, we follow the definition of the Business Dynamics Statistics (BDS). In particular, we define job creation (JC_t) as the sum of all the job gains from expanding firms from year $t-1$ to year t , i.e., the sum of all the jobs created by firms with positive employment growth. In a similar way, job destruction

FIGURE 16 – DISPERSION OF GROWTH RATES OF EMPLOYMENT AND MEAN WAGES BY FIRM’S AGE



Note: Figure 15 shows the 90th-to-10th percentile differential for the cross sectional distribution of one-year log employment change (left panel) and the cross sectional distribution of one-year log real mean wage change (right panel) for five different age groups. Shaded areas represent NBER recession years.

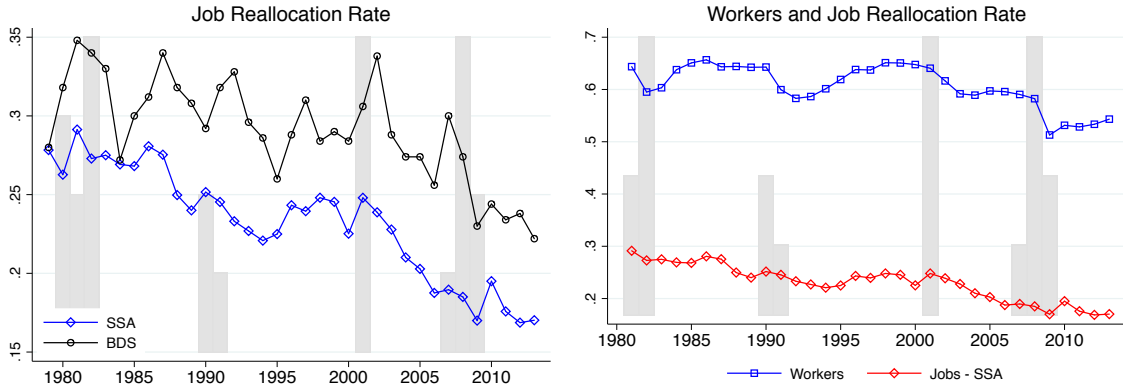
(JD_t) is the sum of all the jobs lost from contracting firms from year $t - 1$ and t , i.e., the sum of all the jobs destroyed by firms for which employment growth is negative. Net job creation (N_t) is the difference between job creation and job destruction. Hence, job reallocation is defined as:

$$JR_t = \frac{JC_t + JD_t - |N_t|}{0.5 \times (E_t + E_{t-1})}, \quad (2)$$

where E_t is the sum of total employment across all the firms in period t . The left panel of figure 17 compares the job reallocation obtained from our data and the corresponding value calculated from the BDS. Since the latter is based on establishment data, the BDS measure predictably generates a larger amount of reallocation, since workers are more likely to move between establishments than between firms, especially when firms are very large. Independently of level differences, both series display a similar decline over the last 30 years (the decline is around 0.10). In the Appendix, Figures A.2 to A.3 show similar measures of reallocation for firms in different sectors and sizes. The overall picture that we draw is one of declining churning/turnover – this is part of the general argument of declining dynamism or fluidity of the US labor market pointed out by Haltiwanger et al. (2015) and others.

One of the main advantages of our data set is that we can follow individuals across multiple firms, that is, we can construct measures of workers reallocation. Measuring workers reallocation is conceptually different than job reallocation as the first follows

FIGURE 17 – JOB AND WORKERS REALLOCATION – SSA AND BDS



Note: The left panel of figure 17 shows the job reallocation calculated as in equation (2) and the same measure of job reallocation as reported by the BDS. The right panel of figure 17 shows the workers reallocation measured as the ratio of the total number of individuals that changed employer between periods $t - 1$ and t over the total average employment.

individuals instead of job positions. Consider for instance a case in which, at period t , firms A and B have the same number of employees. Then, at the end of period t , all the workers of firms A move to B and vice versa. In such case, job creation and job destruction for both firms will be exactly equal to 0 since employment growth is 0, and consequently, job reallocation will be equal to 0, despite the fact that there was a massive reallocation of workers between the two firms.

Calculating how much workers reallocation requires to identify when an individual has switched firm. Here we follow a very simple approach and consider that an individual has changed firms between periods $t - 1$ and t if there was a change in the EIN that provided the maximum amount of earnings (among all the EIN for which the individual worked) between periods $t - 1$ and t . Individuals that move from or to non employment are not considered in the analysis.

Then, we calculate the total number of workers switching of employer between period $t - 1$ and t and we define this as our measure of total workers reallocation, WR_t . Similarly to the job reallocation rate, the workers reallocation rate is the ratio between WR_t and the average number of workers in periods t and $t - 1$. Notice that the workers reallocation rate can be bigger than 1 (as in the simple example with two firms) and larger than the job reallocation rate. In fact, we find that workers reallocation is larger than job reallocation, as it is shown in the right panel of figure 17. As in the case of the job reallocation rate, workers reallocation is declining over time. This is also observed within 1-digit SIC industries (figure A.12), and within different age groups (left panel of figure A.13). We

also find similar results if we restrict the sample to individuals with only one EIN per year (right panel of figure [A.13](#)).

4 Why Do Survey Data Tell a Different Story?

To analyze the properties of the distribution of earnings growth one needs access to longitudinal data on individual workers. Since the availability of large scale administrative records is a recent phenomenon (at least for the United States), most of the early research on income volatility has been based on survey data, such as the CPS, the SIPP, or the PSID. Then, a major question is thus, why does survey data show rising earnings growth variance while administrative data shows this is falling?

One possible explanation for the difference is the rising shares of imputed earnings due to rising item non-response ([Meyer et al. \(2015\)](#)). Imputed earnings values generate much higher levels of earnings dynamics since imputed values contain more measurement error, leading to large time series changes. Moreover, most of the imputed earnings comes from the tails of the income distribution, so that the imputation process used to replace missing individuals generates particularly large changes in earnings for these individuals. Because of these issues most recent papers—like [Ziliak et al. \(2011\)](#)—do not use imputed records.

Another possible explanation is rising non-response rates. As [Meyer et al. \(2015\)](#) show, non-response has increased markedly in all household surveys. While it is unclear exactly why this has occurred they offer a variety of possible reasons, including individuals being too-busy, rising survey fatigue from more commercial surveys, greater concerns over privacy, or the rising challenge of accessing people due to the disappearance of land-lines and the spread of gated communities. If this rising non-response is non-random—for example, if college-educated employees, who have particularly low income variance, are also particularly afflicted by rising non-response due to their rising working hours and earnings—this could bias trends in survey earnings variance.

Finally, there is some evidence that survey response quality deteriorates with non-response, in the sense that the public is less keen to fill out surveys, are more likely to skip individual questions, and take less care completing the questions they do fill in ([Meyer et al. \(2015\)](#)). This would directly increase survey earnings variance by raising earnings measurement error.

4.1 Earnings growth dispersion in the matched CPS sample

We start by analyzing trends in earnings volatility in the CPS. We use a sample of individuals from the March Supplement of the CPS between 1980 and 2014. Because of the rotating design of the CPS, a respondent is in the sample for 4 months, out 8 months, and interviewed again for 4 additional months. This makes possible to match approximately one-half of the sample from one March interview to the next. The CPS data carry two types of imputation flags: earnings imputation and whole-observation imputation. The first indicates if an individual failed or refused to answer the earnings question of the CPS. The second indicates if an individual was not found or refused to answer any of the questions in the CPS.

As we show below, the way that we treat the imputed earnings in our sample has significant implications for the trend of earnings growth dispersion in the CPS. The initial rotating sample includes about 20,000 observations per year. However, after restricting the sample to individuals between 25 and 64 with an income level above the same time-varying threshold that we used to select our SSA sample, we end up with nearly 12,000 observations per year.

Using this sample, we calculate the earnings growth of an individual as the log-difference of real wage and salary earnings between periods t and $t + 1$, and we measure dispersion in the same way as we did with our SSA for two samples: (a) the entire matched sample, and (b) a sample where individual with allocated earnings (imputed earnings or whole case imputation) have been eliminated. In figure 18 we show the dispersion of earnings for the matched March-CPS sample. It is clear from the picture that including allocated earnings has a large impact not only on the level of earnings volatility, but also in its trend, which flattens out substantially when individuals with allocated earnings are excluded.

The difference between the measures of dispersion in the two samples (with and without allocated earnings) comes from three factors: (a) sample attrition, (b) the way in which Census deals with missing observations, and (c) the increase in the frequency of these observations over time. First, imputation in the CPS sample is not random but correlated with the level of income of individuals. To see this, the upper left panel of figure 19 shows the proportion of allocated individuals within percentiles of the income distribution, pooling data for all years. There is a clear U-shape pattern, implying that individuals with allocated earnings tend to come disproportionately from the tails of the

earnings distribution.

Second, the Census and the Bureau of Labor Statistics use an imputation process known as Hot Deck Imputation, which uses information from individuals in the sample with non-missing earnings records (the “donors”) to impute earnings for individuals with missing records (the “receivers”). This process works quite well if the goal is to replicate the distribution of income levels since, in practice, it consists of assigning to individuals with missing records the earnings of observationally equivalent individuals (with similar characteristics in terms of age, education, location, etc.).

However, the Hot Deck Imputation method can have a potentially larger (and misleading) impact on the measured growth rate of earnings. This is visible from the upper right panel of figure 19. The graph plots income in period $t + 1$ against income in period t . Consider first the relation for people with non-allocated earnings in period $t + 1$. Due to mean reversion, individuals at the bottom (top) of the distribution are likely to experience an increase (decrease) in their earnings. However, this mean reversion is severely exacerbated for individuals with allocated earnings in period $t + 1$. The reason is that individuals with allocated earnings are disproportionately coming from the tails, and the Hot Deck Imputation imputes them the earnings of a “normal” donor—one who experiences small growth in his/her income. Hence, this almost mechanically generates a larger dispersion of earnings growth rates. If the proportion of imputed observations is growing over time, it is clear how one could obtain an increasing volatility trend as shown above even when none exists. Indeed, the bottom panel of figure 19 shows that the proportion of individuals with allocated earnings is increasing, going from 24% to 32% between 1997 and 2014.

These results show that one should exercise caution in using survey data to calculate growth rates of income, especially when using data that have been imputed. Moreover, if the proportion of missing observations and nonresponse increases over time, which is the case of all the major surveys in the US (see [Meyer et al. \(2015\)](#)), extra caution must be taken, as the imputation process can generate large biases in levels and trends.¹⁰

¹⁰The increasing rate of nonresponse is not an exclusive problem of the CPS but has been observed in most of the major survey in the U.S. such as the Survey of Consumer Finances, the Consumer Expenditure Survey (diary and quarterly), among others. See [Massey and Tourangeau, eds \(2013\)](#) for an extensive discussion on the topic.

FIGURE 18 – DISPERSION OF EARNINGS GROWTH IN THE MATCHED CPS SAMPLE

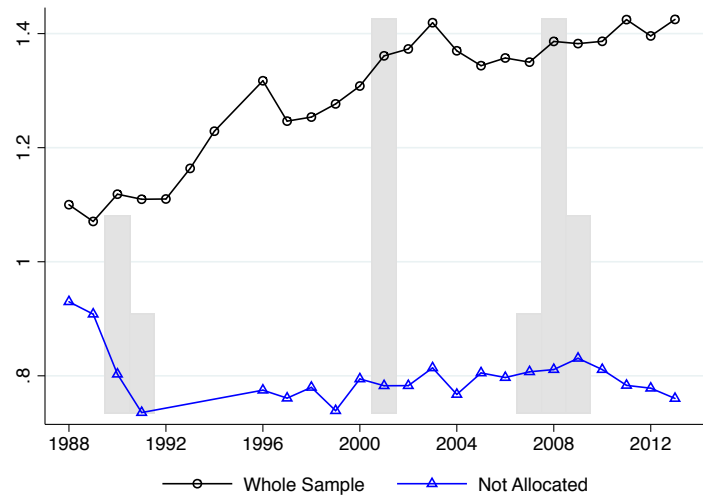
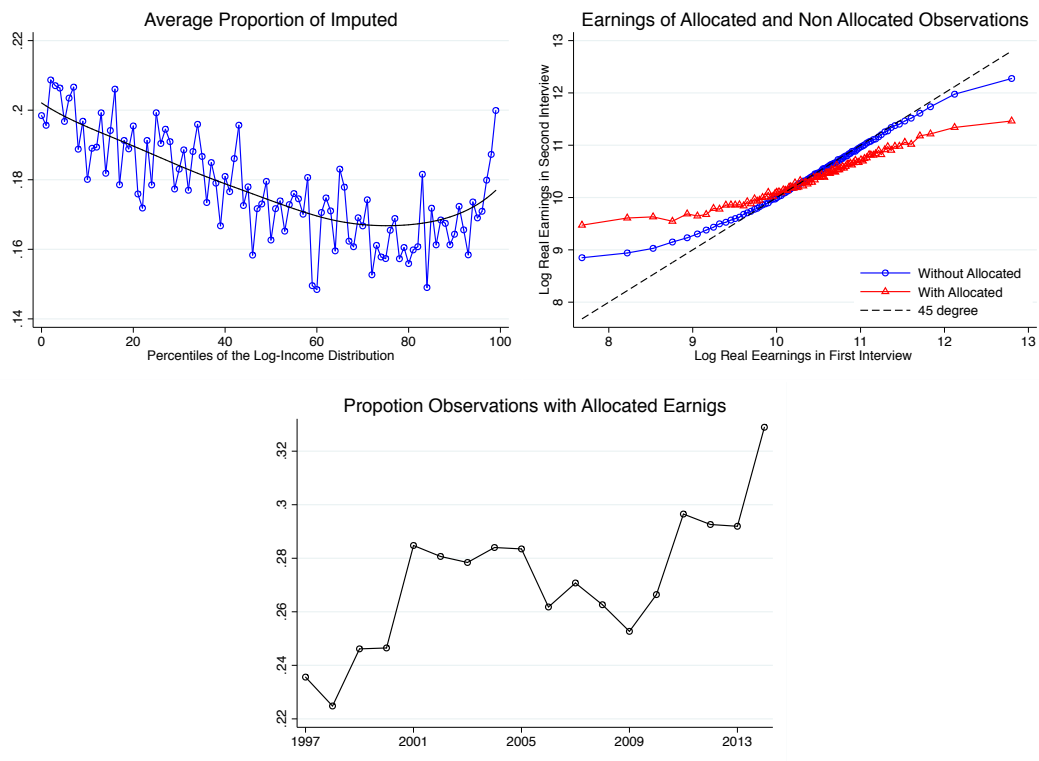


FIGURE 19 – PROPORTION OF ALLOCATED OBSERVATIONS MATCHED CPS SAMPLE AND EARNINGS DISTRIBUTION



5 Composition Effects

Economists have long recognized that earnings growth differ substantially between workers that keep stable employment relationships and workers that switch jobs (see e.g. [Topel and Ward \(1992\)](#) or the more recent work of [Bagger et al. \(2014\)](#)). This generates that the dispersion of earnings growth rates among job-switchers is substantially higher than for job-stayers. However several questions remain un answered, for instance, has the share of individuals switching jobs decreased over time? How the dispersion within each group has evolved? Do these changes have any role for explaining the trends in volatility documented in the previous section? Here we address these issues exploiting the matched employer-employee nature of our data set.

We start by looking at how the dispersion of earnings growth for stayers and switchers has changed over time and disentangle the relative contribution of each group to the total dispersion of earnings growth. Since an individual may hold multiple jobs during a year (and some of this jobs may be of short duration), we need to take a stand about what constitutes a job switch. Here we consider a simple classification: we classify an individual as “job-stayer” in period t if the same EIN provided the largest amount of income (out of all EIN’s from which the individual received earnings in a particular year) between years $t - 2$ and $t + 1$. A worker is classified as “job switcher” if she is not a “job-stayer”.¹¹ Notice that individuals that exit the market during an entire year (do not receive any income during an entire year) are classified as job switchers.

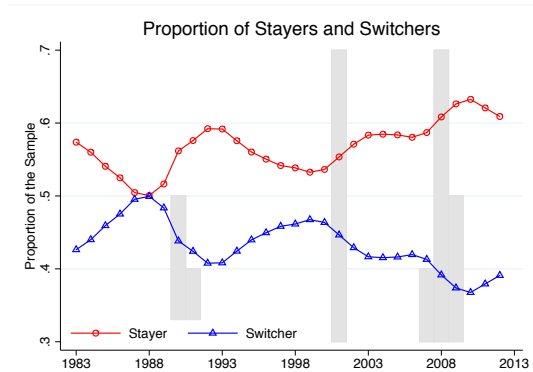
Using this definition we find that the share of job stayers has increased substantially over time from around 50% in 1980 to more than 60% in 2010 as it is shown in [Figure 20](#).¹² This declining trend in the number of job switchers (the complement of our measure of stayers) is similar to the decline of workers reallocation discussed in [section 3.2.2](#) and to the decline of job churning documented by [Davis and Haltiwanger \(2014\)](#), [Decker et al. \(2015\)](#), and others and plays an important role in the drop of the dispersion of income growth as we discuss below.

[Figure 21](#) displays the dispersion for all the workers in the sample, and for job switch-

¹¹We have considered several plausible definitions of job switchers and stayers and found qualitatively similar results. For instance, we have limited our analysis to individuals who have only one job in a given year, finding very similar results. The bulk of workers in the United States (around 95%) have at most two jobs in any given year.

¹²In the [appendix A](#) we show that the proportion of stayers has increased particularly among individuals of 35 years old or more ([figure A.4](#)).

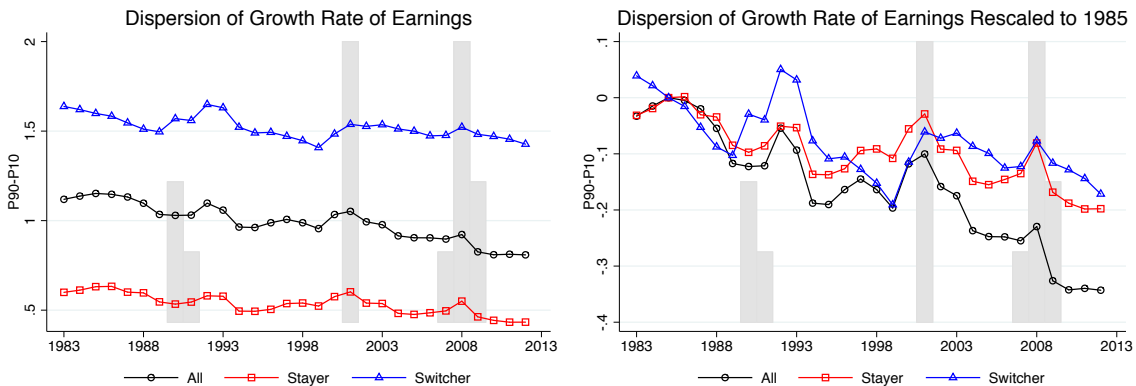
FIGURE 20 – PROPORTION OF SWITCHERS AND STAYERS



Note: Figure 20 shows the time series of the proportion of stayers and switchers. A worker is defined as stayer in year t if the same EIN provided the largest amount of income (out of all the EIN's from where the individual received earnings) between periods $t - 2$ and $t + 1$ (for a total of four periods). An individual is classified as switcher if she is not a stayer. Shaded areas represent NBER recession years.

ers and job stayers separately. The cross sectional dispersion of earnings growth for switchers is three times larger than the dispersion of stayers. However, both groups display a similar declining trend. This is better seen in the right panel of figure 21, which plots the measures of dispersion relative to the value in 1985. Notice that the $P9010$ for the entire sample (the circled line) falls faster than for the two groups separately, especially after 2000. This is partly due to compositional changes (see below). We find similar patterns if we look at the dispersion of stayers and switchers within age groups (see figure A.4) and if we look separately at the dispersion above and below the median (see figure A.6).

FIGURE 21 – DISPERSION OF EARNINGS GROWTH FOR STAYERS AND SWITCHERS



Note: The left panel of figure 21 shows the 90th-to-10th percentile differential for the cross sectional distribution of one-year log real earnings change for stayers and switchers separately. The right panel shows the same statistics re scaled to its 1985 value. Shaded areas represent NBER recession years.

What part of the decline in dispersion can be attributed to compositional changes (i.e., a reduced incidence of job switching) and which part can be attributed to changes in earnings instability within the two groups? Since our sample is a matched employee-employer dataset, we are able to identify transitions within and across firms and in and out of employment. In our data set we can identify four types of transitions between years t and $t + 1$: job stayers (individuals that stay in the same firm j in both periods, denoted by a (E_j, E_j) transition), job switchers (individuals that move from firm j to firm k , that is, a (E_j, E_k) transition), move into non employment (a (E_j, U) transition), and entrants into employment (a (U, E_j) transition).¹³

Using a simple variance decomposition, we can evaluate the relative importance of each of these transitions on the unconditional dispersion of earnings growth. Since individuals with (U, E_j) and (E_j, U) transitions have missing earnings in at least one period, we impute a value of zero for those earnings and we calculate the growth rate of earnings between periods t and $t + 1$ using the arc-percent measure of growth, dw_{it} . Then, the variance of the arc-percentage change earnings can be decomposed into:

$$\text{Var}(dw_{it}) = \mathbb{E}[\text{Var}(dw_{it}|P)] + \text{Var}(\mathbb{E}(dw_{it}|P)), \quad (3)$$

where P is the set of the four possible transitions described above. The first term of the right-hand side is the expected conditional variance of earnings growth, or the *within*-groups component, while the second term is the variance of the conditional expectation of earnings changes, or the *between*-groups component.

Denote the probability of observing an individual moving from non employment to employment in firm j as $\mathbb{P}(U, E_j)$, and denote in similar way the other transition probabilities. Then, it follows that the first term on the right-hand side of expression (3) can be written as:

$$\begin{aligned} \mathbb{E}[\text{Var}(dw_{it}|P)] &= \mathbb{P}(U, E_j) \text{Var}(dw_{it}|U, E_j) + \mathbb{P}(E_j, E_j) \text{Var}(dw_{it}|E_j, E_j) + \\ &\quad \mathbb{P}(E_j, E_k) \text{Var}(dw_{it}|E_j, E_k) + \mathbb{P}(E_j, U) \text{Var}(dw_{it}|E_j, U) \end{aligned}$$

¹³Because our data comes from annual EIN records, we are not able to identify non-employment (NE) spells within a year. Therefore, an individual is identified as moving from employment in year t to non employment in year $t + 1$ (or vice versa) when he does receive W2 income in period t (period $t + 1$) but does not receive any W2 income in period $t + 1$ (period t). Moreover, we are not able to identify NE-to-NE transitions.

but since arc-percent change assigns a value of 2 to each individual that transits from non employment to employment and -2 to individuals transiting from employment to non employment, the first and last term are equal to 0, and the expected conditional variance of earnings change is influenced only by individuals who experience a within- or between-firms income change:

$$\mathbb{E}[\text{Var}(dw_{it}|P)] = \mathbb{P}(E_j, E_j) \text{Var}(dw_{it}|E_j, E_j) + \mathbb{P}(E_j, E_k) \text{Var}(dw_{it}|E_j, E_k).$$

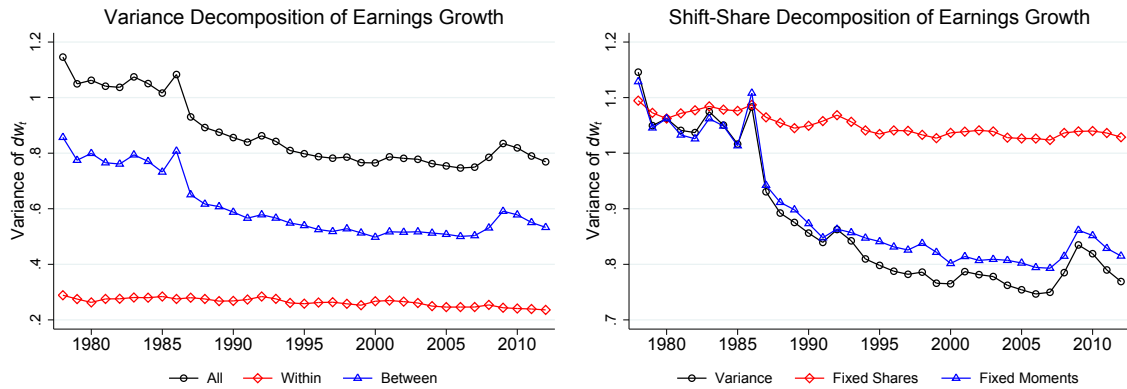
Importantly, $\text{Var}(dw_{it}|E_j, E_j)$ measures the dispersion of earnings growth within firms, while $\text{Var}(dw_{it}|E_j, E_k)$ measures the dispersion of earnings between firms. In light of the previous results, it is very likely that both variances, and their relative weight (the probabilities of each transition), have contributed substantially to the decline of the unconditional dispersion. The second term on the right-hand side of equation (3) can be decomposed into:

$$\begin{aligned} \text{Var}(\mathbb{E}(dw_{it}|P)) &= \mathbb{P}(U, E_j) (\mathbb{E}(dw_{it}|U, E_j) - \mathbb{E}(dw_{it}))^2 + \mathbb{P}(E_j, E_j) (\mathbb{E}(dw_{it}|E_j, E_j) - \mathbb{E}(dw_{it}))^2 \\ &\quad + \mathbb{P}(E_j, E_k) (\mathbb{E}(dw_{it}|E_j, E_k) - \mathbb{E}(dw_{it}))^2 + \mathbb{P}(E_j, U) (\mathbb{E}(dw_{it}|E_j, U) - \mathbb{E}(dw_{it}))^2, \end{aligned}$$

where each term is different from 0. These expressions show how the evolution of the variance of earnings growth can potentially be affected by the composition of the work force. In particular, the large increase in the proportion of job stayers relative to the proportion of job switchers, and the increasing number of individuals that move out of the labor force, could affect the trends in income growth dispersion in important ways.

In fact, the decline of the variance of earnings growth among job switchers and the increase in the share of job-stayers are the two main drivers of the decline of earnings growth volatility. Figure 22 uses the decomposition in expression 3 to show two important results. The left panel shows that the *between*-groups accounts for most of the *level* of the unconditional variance of earnings growth, and it also accounts for the vast majority of its decline, as the within-groups variance has stayed relatively flat during the sample period. To have a sense of the magnitudes of the change, between 1980 and 2005 the cross sectional variance decreased from 1.06 to 0.79, the between groups variance declined from 0.79 to 0.5, while the within groups stayed almost constant going from 0.26 to 0.24. In other words, it is the composition of the population between job stayers and job

FIGURE 22 – DECOMPOSITION OF THE VARIANCE OF EARNINGS CHANGE



Note: The left panel of figure 22 shows the variance of the cross sectional distribution of the one-year changes of log real earnings and its decomposition in the within and between groups components as in equation (3). The right panel shows the counterfactual variance under the assumptions of fixed within group variances or fixed transition probabilities.

switchers what seems to be driving most of the decline of earnings volatility. To strength this point, the right panel of 22 shows a simple counterfactual exercise. The circled line reproduces the main fact: dispersion in earnings growth has declined. The squared line shows how the variance of earnings growth would have evolved if we had kept the transition probabilities fixed at their 1980 values. In other words, we are asking how much of the decline in volatility can be explained by a decline in volatility within each group (job stayers, job switchers, etc.). Clearly, the decline would have been quite modest. On the other hand, the blue line with triangles reports a counterfactual exercise in which we keep within-group conditional means and variances constant, but vary the transition probabilities. This case almost exactly reproduces the unconditional variance of earnings —indicating that the bulk of the decline in earnings volatility is due to changes in the transition probabilities.

As we show in the appendix, these results are robust if we consider different definitions of job switchers. Our results are also robust if we look at stayers and switchers within different age groups. This is an important dimension to consider since it is well established that young workers have faster transitions across jobs than older workers (something that is true in our data as well). Finally, we find similar patterns if we look at individuals across different industries, and if we break down the sample by firm size or age.

To sum up, four types of labor force transition are observed in the data: job stayers, job switchers, move into unemployment, and entrants into work. Each group has an

associated wage volatility. Our main finding is that, while within-group volatility has remained fairly constant over time, the probabilities of being in these four groups have changed over time. In particular, high-volatility types become less frequent, while low-volatility types become more frequent, determining a decline in average volatility.

6 The Joint Dynamics of Firms and Individuals

In this last section we put together the trends in wage and firm outcomes dispersion that we have documented above. The question we want to address here is whether there is a link between the trends of individual’s wage volatility and the trends in employment volatility at the firm level. Other papers have tried to address this question, however, the empirical controversy over whether the two types of volatility measures have declined or increased has also affected discussion. [Comin et al. \(2009\)](#), for example, use survey-based evidence on earnings volatility (as in [Gottschalk and Moffitt \(1994\)](#)) and document increasing earnings dispersion; and use public listed companies data to document increasing employment volatility. The authors lack direct information about the firms individuals work for —and hence have to resort to industry-based regressions. They argue that increased wage volatility is caused by increased employment volatility due, for instance, to increasing reliance on relative performance evaluation schemes. A similar mechanism may be at play in our case. However, given our evidence of declining volatility in both wages and employment growth, it may work exactly in reverse.

Our matched individual-firm dataset allow us to analyze how the dispersion of firm-level outcomes relates to the dispersion of workers level outcomes directly. To our knowledge, this is the first paper to analyze jointly business and earnings growth dispersion in a linked employer-employee dataset for the United States.¹⁴ We start by looking at the bivariate within-industry association between employment growth dispersion and earnings growth dispersion. [Figure 23](#) shows the relation between the $P9010$ of the employment growth distribution (a firm-level variable) and the $P9010$ of the earnings growth distribution (an individual level variable) within 1-digit SIC groups (left panel), and 2-digit SIC groups (right panel). In these plots, each data point is weighted by sector size (measured in terms of the total number of workers on a year-SIC pair) so that bigger

¹⁴Using a matched employee-employer matched dataset for a sample of firms and workers of Italy, [Guiso et al. \(2005\)](#) study the degree of insurance that the firm provide to its worker.

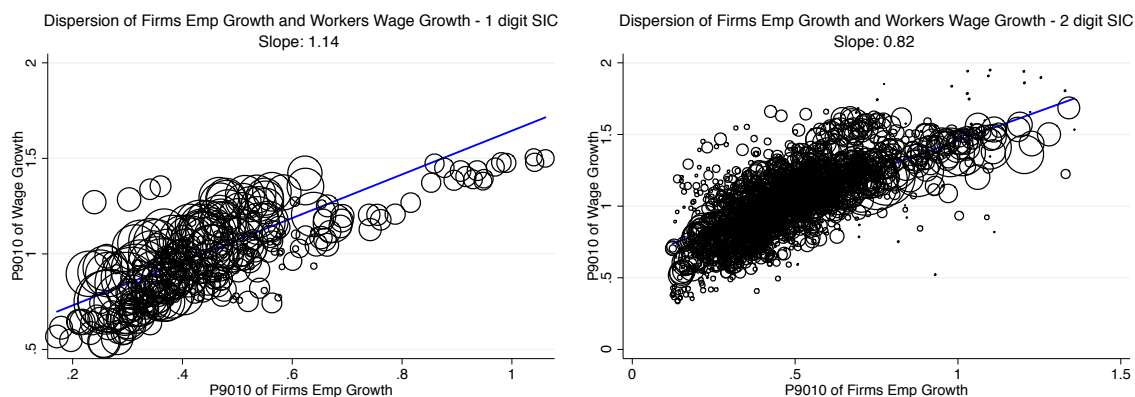
circles correspond to larger sectors. Clearly, there is a strong relation between the two series. However, the relation is affected by the common declining trend discussed in the preceding sections. Moreover, it could be the case that some sectors are inherently more volatile than others both in terms of employment and wages for reasons that cannot be captured by a simple correlation. To control for such factors, and the common trend, we run the following OLS panel regression:

$$\sigma_{j,t}^w = \sigma_j^e + \alpha_0 + d_j + \sum_{\tau=1978}^{2012} c_\tau + X'_{jt}\gamma + \epsilon_{j,t},$$

where $\sigma_{j,t}^w$ is a measure of dispersion of the growth rate of earnings among individuals working in sector j in period t and σ_j^e is the corresponding measure of dispersion of the employment growth across all the firms operating in the sector j in the same time period; d_j is a sector-fixed effect, c_τ a set of year dummies, and X_{jt} a set of sector-level variables that control for age, education, and gender composition of the workforce, and size and maturity of the firms within the sector. The top panel of table **I** (panel A) shows the results for our preferred measure of dispersion, the 90th-to-10th percentiles differential. The first column reproduces the sample correlation between employment and earnings growth dispersion since there are no controls. In the second column we control for time and industry fixed effects. This eliminates the influence of common time trends and sector-specific permanent differences in volatility; not surprisingly, the coefficient drops from 1.14 in column (1) to 0.425 in column (2), although it retains its economic and statistical significance. The interpretation of this estimate is that a 10% increase in the dispersion of employment growth increases the dispersion of earnings growth by about 4%. Adding additional controls, such as the age and size composition for the firms within the sector, the gender composition of the workforce, its age or educational composition (column (4)) does not change substantially the magnitude of the coefficient associated with the volatility of employment growth.

The middle and bottom panels of table **I** look at the dispersion below and above the median, measured by the 50th-to-10th percentiles differential and 90th-to-50th percentiles differential respectively, to study how the two tails of the distribution contribute to our results. In the middle panel we regress a measure of the frequency of left-tail wage adjustments at the sectoral level (the frequency and size of wage cuts) on the frequency of large firm contractions. Focusing in column (7), that industry and year control, we find that an increase in the probability of firm contraction at the sectoral level induces an

FIGURE 23 – DISPERSION OF EMPLOYMENT GROWTH AND EARNINGS GROWTH



Note: Figure 23 shows the correlation of employment growth dispersion and wage growth dispersion within 1-digit and 2-digit SIC groups. Each observation is a year-SIC cell weighted by its employment size.

increase in the probability of wage cuts at the individual level: the estimated coefficient is positive and economically significant. But there are asymmetric effects. In sectors in which there is a larger incidence of expanding firms, measured by the dispersion above the median (the 90th-to-50th percentiles differential), there is no higher probability of wage hikes: the coefficient in column (7) at the bottom panel of table I is not statistically significant and half the magnitude of the coefficient in the middle panel.

For further robustness, in tables II and III we show that using leads and lags of the dispersion of employment growth, instead of contemporaneous correlations, do not alter substantially our results. Our results are also robust to consider 2-digit SIC cell or accounting for entry and exits, as it is shown in the appendix table IV. Table V complements this analysis using measures of sectoral performance such as average stock returns or market value growth. Importantly, we find that measures of sectoral performance are negatively correlated to the dispersion of earnings growth.

In current work we are examining these regressions at the firm level—for example, regressing earnings volatility of continuing employees at a firm on the employment volatility of the firm over matching 10 year panels finding highly significant correlations—but need to address obvious concerns about causality.

7 Conclusions

This paper documents that individual income volatility in the United States has declined in an almost secular fashion since 1980—a phenomenon that we call the “great micro moderation.” This finding contrasts with the conventional wisdom, based on studies using survey data, that income volatility—which is typically taken as a strong indicator of income uncertainty—has increased substantially during the same period. The finding of declining volatility is consistent with a handful of recent papers from administrative data. We substantially extend the existing empirical findings on declining volatility using data from both administrative and survey-based data sets. A key contribution of our paper is to link patterns of income volatility on the worker side to the outcomes (and volatility) on the firm/employer side. Using the information revealed by these linkages, we investigate several potential drivers of this trend to understand if declining volatility represents a broadly positive development—declining income risk and uncertainty—or a negative one, i.e., declining business dynamism.

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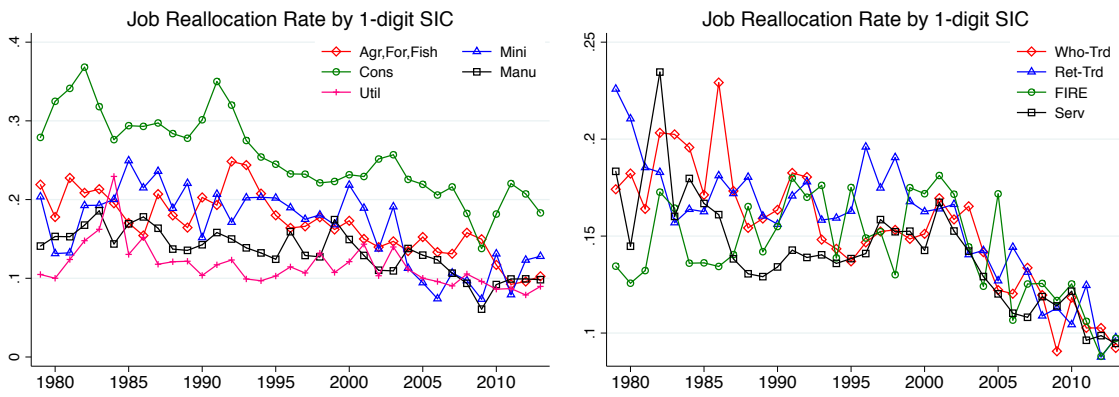
FIGURE A.1 – DISPERSION OF THE GROWTH RATE OF EMPLOYMENT AND MEAN WAGE



Note: The left panel of figure A.1 shows the 90th-to-10th percentile differential of the cross sectional distribution of one-year log change of employment growth and one-year log change of average real wages at the firm-level. The right panel shows the same measures for five-year log changes. Shaded areas represent NBER recession years.

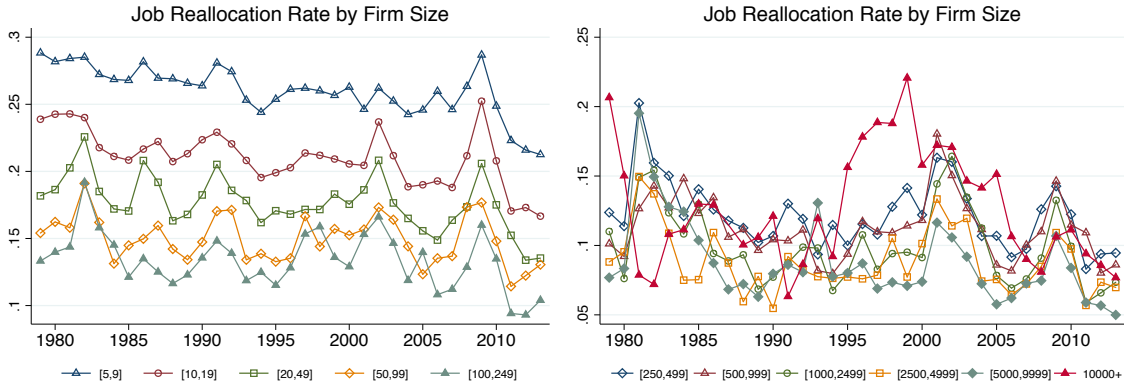
A Appendix: Robustness Figures

FIGURE A.2 – JOB REALLOCATION RATE BY 1-DIGIT SIC



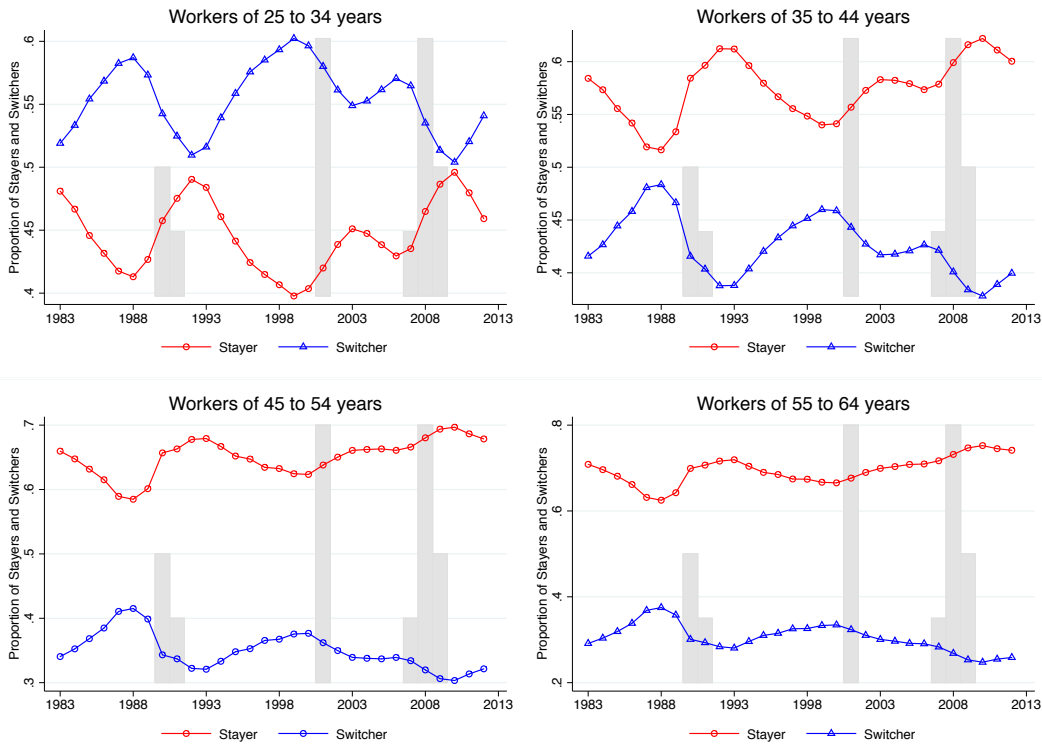
Note: Figure A.2 shows the job reallocation calculated as in equation (2) within 1-digit SIC industries.

FIGURE A.3 – JOB REALLOCATION RATE BY FIRM SIZE



Note: Figure A.3 shows the job reallocation calculated as in equation (2) within different employment size group. The size of a firm is the total number of employees that the firm had during the year.

FIGURE A.4 – PROPORTION OF SWITCHERS AND STAYERS BY AGE GROUP



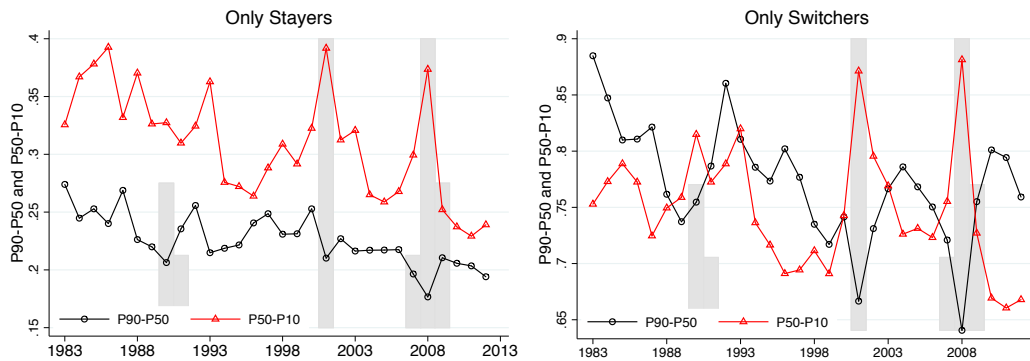
Note: Figure A.4 shows the proportion of switchers and stayers for different age groups. A worker is defined as stayer in year t if the same EIN provided the largest amount of income (out of all the EIN's from where the individual received earnings) between periods $t - 2$ and $t + 1$ (for a total of four periods). An individual is classified as switcher is she is not an stayer. Shaded areas represent NBER recession years.

FIGURE A.5 – RESCALED DISPERSION OF SWITCHERS AND STAYERS BY AGE GROUP



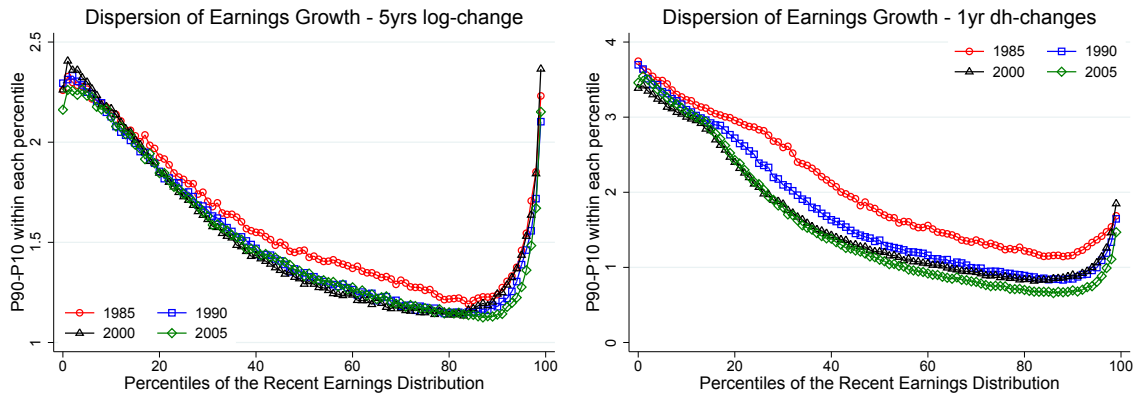
Note: Figure A.5 shows the 90th-to-10th percentile spread of the cross sectional distribution of one-year log change of real earnings for switchers, stayers, and for all workers, within different age groups. A worker is defined as stayer in year t if the same EIN provided the largest amount of income (out of all the EIN's from where the individual received earnings) between periods $t - 2$ and $t + 1$ (for a total of four periods). An individual is classified as switcher is she is not an stayer. Shaded areas represent NBER recession years. Statistics are re scaled by their corresponding value in 1985.

FIGURE A.6 – LEFT AND RIGHT TAIL DISPERSION OF THE GROWTH RATE OF EARNINGS GROWTH



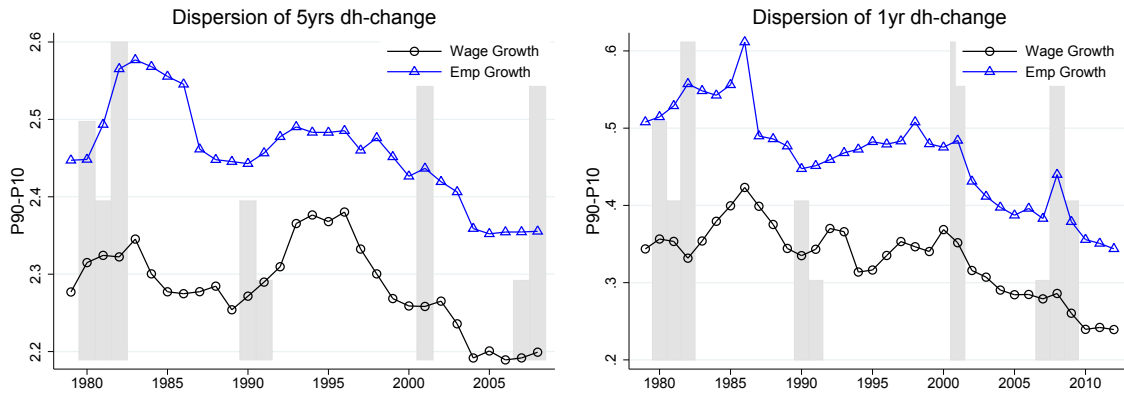
Note: The left panel of figure A.6 shows the 90th-to-50th and 50th-to-10th percentile spreads for individuals classified as stayers. The right panel does the same for switchers. A worker is defined as stayer in year t if the same EIN provided the largest amount of income (out of all the EIN's from where the individual received earnings) between periods $t - 2$ and $t + 1$ (for a total of four periods). An individual is classified as switcher is she is not an stayer. Shaded areas represent NBER recession years.

FIGURE A.7 – EARNINGS DISPERSION BY RECENT EARNINGS – 5YRS CHANGE AND DH CHANGES



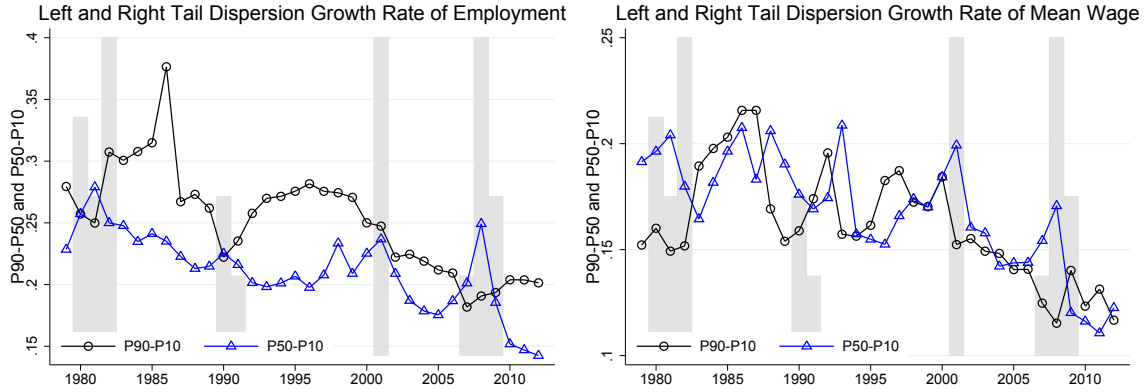
Note: The left panel of figure A.7 shows the 90th-to-10th percentile differential of the cross sectional distribution of the five-year log change of real earnings conditional on the distribution of recent earnings for selected years. For each individual, recent earnings in period t are defined as the average of log-real earnings between periods $t - 1$ and $t - 5$. We drop observations of individuals whose recent earnings were calculated with less than three earnings observations. Dispersion is then calculated using all the growth observations within each percentile of the recent income distribution. The right panel shows the 90th-to-10th percentile different of the one-year arc-percent change for selected years.

FIGURE A.8 – DISPERSION OF THE GROWTH RATE OF EMPLOYMENT AND MEAN WAGE – DH CHANGE



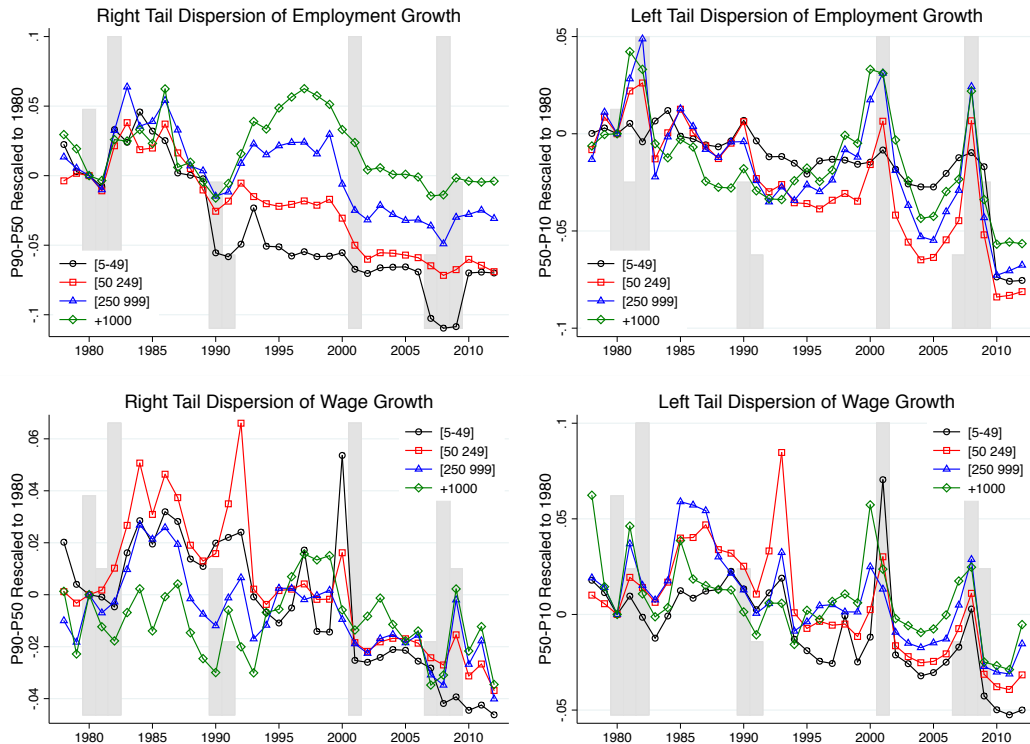
Note: The left panel of figure A.8 shows the 90th-to-10th percentile differential of the cross sectional distribution of the five-year arc-percent change of the firm-level cross sectional distribution of employment growth and mean real wages. The right panel shows the same statistic for the one-year arc-percent change. Shaded areas represent NBER recession years.

FIGURE A.9 – RIGHT AND LEFT TAIL DISPERSION OF GROWTH RATES OF EMPLOYMENT AND MEAN WAGES – DH CHANGE



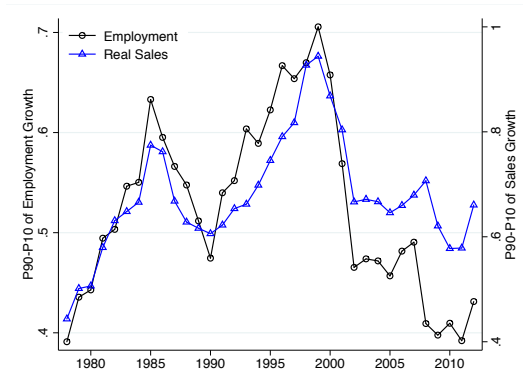
Note: The left panel of figure A.9 shows the 90th-to-50th and 50th-to-10th percentile differential of the firm-level cross sectional distribution of the one-year arc-percent change of employment (left panel) and mean real wage growth (right panel). Shaded areas represent NBER recession years.

FIGURE A.10 – RESCALED LEFT AND RIGHT TAIL DISPERSION BY FIRM SIZE GROUPS



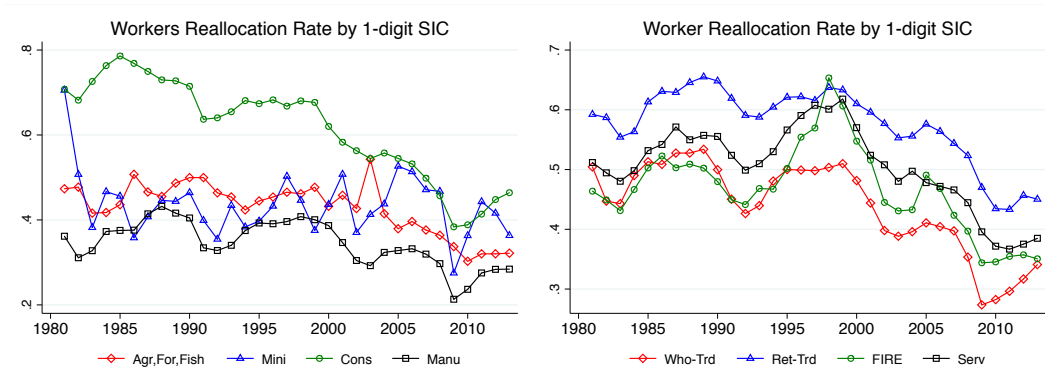
Note: The left panel of figure A.10 shows the 90th-to-50th and 50th-to-10th percentile differential of the firm-level cross sectional distribution of the one-year log-change of employment (upper panels) and mean real mean wage growth (lower panels) by firm size measured by the number of employees. Shaded areas represent NBER recession years.

FIGURE A.11 – DISPERSION OF EMPLOYMENT REAL SALES IN PUBLICLY TRADED FIRMS



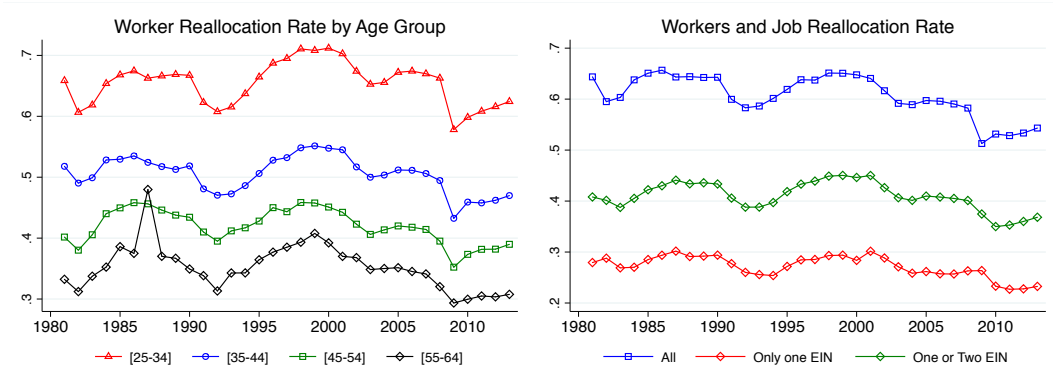
Note: Figure A.11 shows the 90th-to-10th percentile spread of the one year log-change of employment and log real sales for a sample of publicly traded firms. Source: Compustat.

FIGURE A.12 – WORKERS REALLOCATION RATE BY 1-DIGIT SIC



Note: Figure A.12 shows the workers reallocation measured as the ratio of the total number of individuals that changed employer between periods $t - 1$ and t over the total average employment by 1-digit SIC sectors.

FIGURE A.13 – WORKERS REALLOCATION RATE BY AGE GROUPS AND



Note: The left plot of Figure A.13 shows the workers reallocation measured as the ratio of the total number of individuals that changed employer between periods $t - 1$ and t over the total average employment within different age groups. The right panel shows the same measure of workers reallocation restricting the sample to individuals that had one employer each year.

TABLE I – DISPERSION OF WORKERS WAGE GROWTH AND FIRMS EMPLOYMENT GROWTH BY 1-DIGIT SIC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A							
Dependent Variable	$P9010^w_{j,t}$ of Workers Earnings Growth						
$P9010^e_{j,t}$ Employment Growth	1.143*** (0.205)	0.425*** (0.090)	0.486*** (0.116)	0.411*** (0.113)	0.380*** (0.090)	0.353*** (0.099)	0.347* (0.153)
R^2	0.570	0.908	0.909	0.904	0.906	0.908	0.911
N	315	315	315	297	297	297	297
PANEL B							
Dependent Variable	$P5010^w_{j,t}$ of Workers Earnings Growth						
$P5010^e_{j,t}$ Employment Growth	1.149*** (0.136)	0.462*** (0.106)	0.547*** (0.141)	0.467*** (0.113)	0.459*** (0.0997)	0.416*** (0.105)	0.472** (0.158)
R^2	0.544	0.820	0.823	0.813	0.815	0.817	0.824
N	315	315	315	297	297	297	297
PANEL C							
Dependent Variable	$P9050^w_{j,t}$ of Workers Earnings Growth						
$P9050^e_{j,t}$ Employment Growth	1.040*** (0.195)	0.332*** (0.093)	0.291** (0.110)	0.293** (0.120)	0.272** (0.108)	0.275** (0.113)	0.216 (0.158)
R^2	0.370	0.898	0.899	0.895	0.895	0.896	0.898
N	315	315	315	297	297	297	297
Time/SIC FE	N	Y	Y	Y	Y	Y	Y
Controls	None	None	Firm Age/Size	Gender	Indv. Age	Educ.	All

In each of the panels, each column reports the results from a different industry-by-year OLS panel regression. The dependent variable in each column of panel A is the 90th-to-10th percentiles differential the distribution of workers earnings growth within a SIC 1-digit industry-year cell, in panel B the dependent variable is the 50th-to-10th percentiles differential, and in panel C the dependent variable is the 90th-to-50th percentile differential. In each column the main explanatory variable is the corresponding measure of dispersion (90th-to-10th, 50th-to-10th, and 90th-to-50th) of the distribution of firms employment growth within a SIC 1-digit industry-year cell. For all the panels, Column (1) shows the partial correlation between the two measures of dispersion, in column (2) we include year and industry dummies to control for annual and industry fixed effects, in column (3) we control for firms' age and size within each industry-year cell, while in columns (4), (5), and (6) we control for changes in the proportion of women, age groups, and education groups within a SIC 1-digit - year cell. Column (7) includes all the controls at once. Standard errors, shown in parentheses below the point estimates, are clustered at the SIC level. *** denotes 1%, ** denotes 5%, and * denotes 10% significance respectively.

TABLE II – DISPERSION OF WORKERS WAGE GROWTH AND LEADS OF FIRMS EMPLOYMENT GROWTH DISPERSION BY 1-DIGIT SIC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A							
Dependent Variable	$P_{9010}^w_{j,t}$ of Workers Earnings Growth						
$P_{9010}^e_{j,t+1}$ Employment Growth	1.092*** (0.185)	0.337*** (0.0935)	0.359** (0.147)	0.352** (0.134)	0.309** (0.102)	0.299* (0.136)	0.245 (0.191)
R^2	0.523	0.899	0.899	0.896	0.897	0.900	0.904
N	306	306	306	288	288	288	288
PANEL B							
Dependent Variable	$P_{5010}^w_{j,t}$ of Workers Earnings Growth						
$P_{5010}^e_{j,t+1}$ Employment Growth	1.008*** (0.0727)	0.291** (0.120)	0.342* (0.166)	0.421** (0.181)	0.384* (0.190)	0.346 (0.224)	0.346 (0.310)
R^2	0.432	0.800	0.801	0.794	0.796	0.800	0.808
N	306	306	306	288	288	288	288
PANEL C							
Dependent Variable	$P_{9050}^w_{j,t}$ of Workers Earnings Growth						
$P_{9050}^e_{j,t+1}$ Employment Growth	1.004*** (0.200)	0.238** (0.0837)	0.176 (0.0999)	0.213* (0.100)	0.196** (0.0824)	0.193* (0.0933)	0.124 (0.0993)
R^2	0.333	0.892	0.893	0.889	0.890	0.891	0.893
N	306	306	306	288	288	288	288
Time/SIC FE	N	Y	Y	Y	Y	Y	Y
Controls	None	None	Firm Age/Size	Gender	Indv. Age	Educ.	All

In each of the panels, each column reports the results from a different industry-by-year OLS panel regression. The dependent variable in each column of panel A is the 90th-to-10th percentiles differential the distribution of workers earnings growth within a SIC 1-digit industry-year cell, in panel B the dependent variable is the 50th-to-10th percentiles differential, and in panel C the dependent variable is the 90th-to-50th percentile differential. In each column the main explanatory variable is the one-year lead of the corresponding measure of dispersion (90th-to-10th, 50th-to-10th, and 90th-to-50th) of the distribution of firms employment growth within a SIC 1-digit industry-year cell. For all the panels, Column (1) shows the partial correlation between the two measures of dispersion, in column (2) we include year and industry dummies to control for annual and industry fixed effects, in column (3) we control for firms' age and size within each industry-year cell, while in columns (4), (5), and (6) we control for changes in the proportion of women, age groups, and education groups within a SIC 1-digit - year cell. Column (7) includes all the controls at once. Standard errors, shown in parentheses below the point estimates, are clustered at the SIC level. *** denotes 1%, ** denotes 5%, and * denotes 10% significance respectively.

TABLE III – DISPERSION OF WORKERS WAGE GROWTH AND LAGS OF FIRMS EMPLOYMENT GROWTH DISPERSION BY 1-DIGIT SIC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A							
Dependent Variable	$P9010^w_{j,t}$ of Workers Earnings Growth						
$P9010^e_{j,t-1}$ Employment Growth	1.133*** (0.201)	0.373** (0.113)	0.477** (0.160)	0.366** (0.124)	0.329*** (0.093)	0.308** (0.119)	0.367** (0.159)
R^2	0.560	0.905	0.906	0.903	0.904	0.907	0.912
N	306	306	306	297	297	297	297
PANEL B							
Dependent Variable	$P5010^w_{j,t}$ of Workers Earnings Growth						
$P5010^e_{j,t-1}$ Employment Growth	1.072*** (0.096)	0.183 (0.192)	0.243 (0.199)	0.181 (0.196)	0.154 (0.168)	0.117 (0.169)	0.115 (0.181)
R^2	0.468	0.805	0.807	0.802	0.804	0.809	0.816
N	306	306	306	297	297	297	297
PANEL C							
Dependent Variable	$P9050^w_{j,t}$ of Workers Earnings Growth						
$P9050^e_{j,t-1}$ Employment Growth	1.059*** (0.207)	0.358*** (0.071)	0.365*** (0.099)	0.349*** (0.081)	0.329*** (0.076)	0.328*** (0.091)	0.327** (0.115)
R^2	0.385	0.898	0.898	0.896	0.897	0.898	0.899
N	306	306	306	297	297	297	297
Time/SIC FE	N	Y	Y	Y	Y	Y	Y
Controls	None	None	Firm Age/Size	Gender	Indv. Age	Educ.	All

In each of the panels, each column reports the results from a different industry-by-year OLS panel regression. The dependent variable in each column of panel A is the 90th-to-10th percentiles differential the distribution of workers earnings growth within a SIC 1-digit industry-year cell, in panel B the dependent variable is the 50th-to-10th percentiles differential, and in panel C the dependent variable is the 90th-to-50th percentile differential. In each column the main explanatory variable is the one-year lag of the corresponding measure of dispersion (90th-to-10th, 50th-to-10th, and 90th-to-50th) of the distribution of firms employment growth within a SIC 1-digit industry-year cell. For all the panels, Column (1) shows the partial correlation between the two measures of dispersion, in column (2) we include year and industry dummies to control for annual and industry fixed effects, in column (3) we control for firms' age and size within each industry-year cell, while in columns (4), (5), and (6) we control for changes in the proportion of women, age groups, and education groups within a SIC 1-digit - year cell. Column (7) includes all the controls at once. Standard errors, shown in parentheses below the point estimates, are clustered at the SIC level. *** denotes 1%, ** denotes 5%, and * denotes 10% significance respectively.

TABLE IV – DISPERSION OF WORKERS WAGE GROWTH AND SECTORAL DISPERSION BY 2-DIGIT SIC

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$P9010^w_{j,t}$	$P9010^w_{j,t}$	$P9050^w_{j,t}$	$P5010^w_{j,t}$	$P9010^w_{j,t}$	$P9010^w_{j,t}$	$P9050^w_{j,t}$	$P5010^w_{j,t}$
	<i>log – changes</i>							
	Moments of Workers Earnings Growth							
	<i>dh – changes</i>							
$P9010^e_{j,t}$ Employment Growth	1.235*** (0.116)	0.227*** (0.0850)			0.602*** (0.111)	0.151** (0.0626)		
$P9050^e_{j,t}$ Employment Growth			0.133*** (0.0473)				0.0823* (0.0439)	
$P5010^e_{j,t}$ Employment Growth				0.346** (0.138)				0.140** (0.0621)
R^2	0.322	0.890	0.916	0.831	0.389	0.902	0.886	0.828
N	2160	2160	2160	2160	2124	2124	2124	2124
Time/SIC FE	N	Y	Y	Y	N	Y	Y	Y

Each column reports the results from a different industry-by-year OLS panel regression. The dependent variables are cross sectional moments of the 1-year earnings growth distribution for workers within a 2-digit SIC-year cell, while the independent variables are cross sectional moments of the 1-year employment growth distribution for firms within the same 2-digit SIC cell. Standard errors, shown in parentheses below the point estimates, are clustered at the 2-digit SIC level. *** denotes 1%, ** denotes 5%, and * denotes 10% significance respectively.

TABLE V – DISPERSION OF WORKERS WAGE GROWTH AND SECTORAL PERFORMANCE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A							
Dependent Variable	$P9010_{j,t}^w$ of Workers Earnings Growth						
Mean Stock Returns	-0.0535*** (0.0130)	-0.0865*** (0.0306)	-0.0858** (0.0343)	-0.0949*** (0.0305)	-0.0915*** (0.0289)	-0.0840*** (0.0309)	-0.0781*** (0.0292)
R^2	0.00587	0.902	0.903	0.900	0.902	0.905	0.910
N	315	315	315	297	297	297	297
PANEL B							
Dependent Variable	$P9010_{j,t}^w$ of Workers Earnings Growth						
Mean Market Value Growth	-0.0514** (0.0155)	-0.0963*** (0.0332)	-0.0957** (0.0286)	-0.104*** (0.0333)	-0.100*** (0.0316)	-0.0972*** (0.0330)	-0.0960*** (0.0314)
R^2	0.00515	0.902	0.903	0.900	0.902	0.905	0.910
N	315	315	315	297	297	297	297
PANEL C							
Dependent Variable	$P9010_{j,t}^w$ of Workers Earnings Growth						
Dispersion Stock Returns	0.0216 (0.0410)	0.0730** (0.0297)	0.0719 (0.0487)	0.0823*** (0.0302)	0.0773** (0.0304)	0.0829*** (0.0316)	0.0686** (0.0327)
R^2	0.00204	0.904	0.904	0.902	0.904	0.908	0.911
N	315	315	315	297	297	297	297
Time/SIC FE	N	Y	Y	Y	Y	Y	Y
Controls	None	None	Firm Age/Size	Gender	Indv. Age	Educ.	All

In each of the panels, each column reports the results from a different industry-by-year OLS panel regression. The dependent variable in each column of is the 90th-to-10th percentiles differential the distribution of workers earnings growth within a SIC 1-digit industry-year cell. In panel A the main explanatory variable is average annual stock market return within a SIC 1-digit industry-year cell calculated from Compustat. In panel B the main explanatory variable is the average annual growth rate of the market value within a 1-digit SIC-year cell. In panel C we use the dispersion annual stock returns. For all the panels, Column (1) shows the partial correlation between the two measures of dispersion, in column (2) we include year and industry dummies to control for annual and industry fixed effects, in column (3) we control for firms' age and size within each industry-year cell (using data from BDS), while in columns (4), (5), and (6) we control for changes in the proportion of women, age groups, and education groups within a SIC 1-digit - year cell (using data from CPS). Column (7) includes all the controls at once. Standard errors, shown in parentheses below the point estimates, are clustered at the 1-digit SIC level. *** denotes 1%, ** denotes 5%, and * denotes 10% significance respectively.