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Abstract

We show that AI technologies are oriented toward jobs and workers that typically exhibit greater volatility in labor market outcomes over the business cycle. Occupations currently most exposed to AI are those that have historically exhibited (i) greater volatility in employment levels over business cycles, (ii) higher job-switching rates by workers, (iii) higher job-finding rates, and (iv) a lower likelihood for workers to exit the labor force following a job loss. The sectors of the U.S. economy that produce AI technologies have also historically exhibited high volatility in productivity. We then quantify how technology-led structural changes in economic activities contribute to aggregate business cycle volatility. Growth in the production of AI-based technologies in recent years increased the volatility of U.S. output by 2.8 percent, roughly 3.5 times what resulted from the late 1990s' IT boom. If the orientation of AI toward occupations that exhibit higher variability in labor market outcomes results in a higher aggregate labor supply elasticity, the effects on aggregate volatility are even greater.

Keywords: Technological Change, Volatility, Artificial Intelligence (AI)

JEL Classifications: E32,E37,J62,J63,O33

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1 Introduction

The latest AI boom is an ongoing period of technological innovation that is altering the way that a broad swath of work is getting done. The bias of any technological change toward or away from certain occupations determines how labor markets respond, both over the long term and over business cycles. In this article, we show that AI technologies are oriented toward jobs and workers that typically exhibit greater volatility in labor market outcomes over the business cycle. That is, we offer the view that the current AI boom is a period of volatility-biased technological change. Furthermore, we quantify how a technology-led reallocation of activity across sectors, jobs, and workers with different dynamics could shift the aggregate volatility of the U.S. economy.

First, we establish a series of empirical facts about the U.S. labor market. AI-based technologies are more deeply integrated in occupations that historically exhibit (i) greater volatility in employment levels over business cycles, (ii) a higher propensity for workers to quit and switch jobs (i.e., job-to-job transitions), (iii) greater likelihood for workers to find a job regardless of whether they were previously unemployed or out of the labor force, and (iv) a lower likelihood for workers to get stuck on the sidelines by leaving the labor force following a job loss. The disparities are evident for both high-frequency fluctuations in employment outcomes and fluctuations at cyclical frequencies, and across occupations with different degrees of measured AI use. Altogether, these facts motivate our characterization of AI technologies as being biased toward higher-volatility aspects of the U.S. labor market.

Next, we quantify the changes in macroeconomic volatility driven by the onset of new AI technologies. We measure these effects using a straightforward model of the microfoundations of business cycle volatility that builds on Carvalho and Gabaix (2013). Complementary to our findings for labor market volatility, we confirm that the production of AI technologies is oriented toward sectors of the U.S. economy that historically exhibit greater volatility in productivity and real output. The ratio of gross sales to GDP for AI-producing sectors – namely, Information & Data Processing Services sectors – nearly doubled from 1.5% to 3%, significantly more than any other sector, and these sectors exhibit historical volatility that is more than three times that of the median sector. As a result, the underlying volatility of U.S. real output originating solely from these microfoundations rose by 2.8% from 2019 to 2024. This increase in macroeconomic volatility is 3.5 times larger than what occurred on the heels of the IT boom, due to the fact that AI-producing sectors exhibit significantly greater variability in productivity than IT-producing sectors. Moreover, it is equivalent to the entirety of the increase in underlying volatility observed in recent years. While recent changes in output volatility have been more modest than in past decades, the measured differences due solely to the growth in the production of AI technologies are conservative in that they do not account for changes in the variability of labor market outcomes.

The estimated effect of technology-led structural changes in production on volatility is even greater if the orientation of AI use toward workers and jobs exhibiting high labor market mobility results in a higher aggregate labor supply elasticity, as suggested by the empirical facts we establish here. Business cycle volatility is known to be sensitive to the composition of the labor force when workers exhibit different degrees of dynamism (Jaimovich and Siu, 2009). Moreover, the timing of the current AI boom in the U.S. economy – during a period when retirements among the baby boomer generation are pushing down the labor share of income – further exacerbates any increase in aggregate volatility. Intuitively, capital and other non-labor factors of production tend to be more mobile, so that a lower labor share increases the responsiveness of aggregate output to individual sector-specific shocks. Together, the production channel related to the development of AI technologies and the labor market channel resulting from AI use could lead to growth in volatility for the U.S. economy were recent trends to persist.[1] These insights are important for policymakers to recognize because many fiscal and monetary tools are aimed at stabilizing business cycle fluctuations, which could become more volatile in the wake of ongoing technological change.

[1]Certain financial sectors, especially Securities, Commodity Contracts, and Investments (NAICS 523), also made a significant contribution to the underlying volatility of the U.S. economy in recent years. These sectors have large linkages to AI technologies, which is an additional channel we do not disentangle here.

We begin our empirical analysis by measuring cyclical and other higher-frequency variability in U.S. labor market outcomes for specific occupations. The Occupational Employment and Wage Statistics (OEWS) program from the U.S. Bureau of Labor Statistics (BLS) and the Current Population Survey (CPS) from the U.S. Census Bureau serve as the basis for most of our analysis of employment fluctuations and labor force flows across different occupations between 1997 and 2024. The Anthropic Economic Index (AEI) provides information about the extent of user prompts on its AI platforms that are relevant to specific occupations according to O*NET standard occupational classifications (SOC). Specifically, this measure aggregates the use of AI to accomplish a variety of tasks by users in a workplace setting up to the occupational level based on the fraction of occupation-specific time spent on each task. These measures indicate significant differences in the application of AI across occupations that we use to identify the links to various aspects of labor market volatility.

To measure changes in aggregate output volatility, we incorporate direct observations of annual sector-specific total factor productivity growth and gross sales-to-value added pioneered by Dale Jorgensen and reported by the U.S. Bureau of Economic Analysis Integrated Industry Accounts. This "KLEMS" approach traces aggregate GDP growth from its microfoundations in changes in factors of production and total factor productivity. As in Jorgenson et al. (2008) and Carvalho and Gabaix (2013), we use these panel data to construct long histories of output volatility for individual sectors of the U.S economy as well as shifts in activity across sectors during previous episodes of rising and declining volatility. These data allow us to quantify how AI-based technological change has shifted activity toward high-volatility sectors and influenced aggregate volatility. Importantly, the KLEMS approach to measuring sector-specific growth distinguishes between total factor productivity shocks and capital deepening. By focusing on the former we are able to consider the long-term implications of reallocations of activity due to technological change, as fluctuations in output due to capital deepening or changes in labor utilization would largely reflect the (still ongoing) transitional features of the integration of AI technologies into the U.S. economy.

2 Related Literature

This article contributes to a substantial literature on the drivers of macroeconomic volatility. Most closely related to this study, Jaimovich and Siu (2009) demonstrate how demographic changes in the U.S. and G7 countries led to changes in the cyclical volatility of their economies in the post-WWII era. They show that changes in labor force composition across ages – when workers exhibit significant differences in the variability of their employment outcomes – result in changes in business cycle volatility. While they highlight the role of the composition of workers in the labor force as a factor influencing the dynamics of an economy, we highlight changes in the composition of jobs induced by broad-based technological change.

Several prior studies established a link from the microfoundations of labor market activity across workers, jobs, and sectors with different degrees of dynamism to the aggregate volatility of the U.S. economy. Carvalho and Gabaix (2013) argue the period of the Great Moderation in macroeconomic volatility of the U.S. economy beginning in the early 1980s is fully explained by shifts in activity away from sectors that exhibit higher volatility. Moreover, they show how shifts in labor market dynamics, like those we study here, can amplify the manner in which sector-specific volatility influences aggregate business cycle volatility. Koren and Tenreyro (2007) demostrates that countries tend to have different allocations of activity across sectors at different stages of development, and that these differences in diversification generally explain much of the observed variation in macroeconomic volatility between countries.[2] Faberman (2017) further argues the role of reallocative shocks — like technology shocks that shift employment across occupations and sectors — became even more important following the Great Moderation due to reductions in the aggregate cyclicality of job flows.[3] By establishing the bias of AI technologies toward more volatile aspects of

[2]Gabaix (2011) emphasizes that "sectors" of the economy is more general than standard industry classifications, such that the microeconomic foundations of the economy could account for concentrations of activities at very large firms, not just prescribed industries.

[3]Stock and Watson (2002) coined the term "Great Moderation" to describe the decline in volatility that began in the early 1980s, which was initially documented by McConnell and Perez-Quiros (2000) and Blanchard and Simon (2001). An extensive literature on the decline in volatility examines contributing factors distinct from reallocations of activity across sectors, including better inventory management (Irvine

the U.S. labor market, we demonstrate how the ongoing technological change may lead to a shift in aggregate volatility via similar mechanisms described in these previous studies.

This paper also contributes to the corpus of research that characterizes different episodes of technological change. The most prominent example is the recent decades-long episode of skill-biased technological change, as described in Acemoglu (2002) and Autor et al. (2003). Other analyses highlight episodes of technological catch-up during which production techniques pervasive in advanced economies are adopted by less developed countries, leading to convergence in growth rates (e.g., Bernard and Jones 1996). Related, Quah (1996) highlights limits on the propensity for broad-based catch-up to occur, resulting in "twin peaks" in the distributions of growth rates across countries. Kumar and Russell (2002) provide a methodology for distinguishing productivity growth due to technological change versus technological catch up and capital deepening, highlighting the importance of distinguishing these types of changes in production techniques. Another important characterization is the set of technologies that facilitate the relocation of production activities across geographies, such as air conditioning (Biddle, 2011), telecommunication (Grossman and Rossi-Hansberg, 2006), and roads (Duranton et al., 2014). A single characterization of AI-based technological change is likely premature at this point and too limiting since the frontier of the technology is expanding faster than its adoption. Still, the series of empirical facts regarding AI use for jobs and workers as they relate to features of labor market volatility adds new perspective on the long-run implications of the current broad-based technological change.

Finally, the paper hops on the bandwagon of analyses studying the implications of AI for the U.S. labor force. Most of this work is aimed at quantifying the implementation and adoption of AI capabilities across tasks, jobs, firms, or industries, as in Acemoglu et al. (2022), Adams et al. (2026), Eloundou et al. (2024), Felten et al. (2019) & Felten et al. (2019) and Webb (2019). Alternatively, much of the recent literature on AI, and the pervasive punditry, is aimed at highlighting the transitional features of the labor market as the

and Schuh, 2005) and better monetary policy (Clarida et al., 2000), declines in new business formation (Pugsley and Şahin, 2019), among others.

economy responds to the structural shifts in hiring caused by the onset of AI technology. More generally, Kalyani et al. (2025) establish stylized facts on the historical diffusion of jobs related to new technologies. We are agnostic about the final state of employment levels, productivity levels, or AI adoption levels that result from this new technology. The ultimate complementarity or substitution for labor that occurs because of AI is still yet to be determined. Our only aim is to highlight that, were economic activity to continue to shift across occupations and sectors, the result would likely be a change in the aggregate volatility of the U.S. economy due to the nature of current AI technologies being skewed toward workers, jobs and industries that exhibit more volatility over the business cycle.

3 Data and Measurement

This analysis requires measurement of two distinct features of the U.S. labor market: (i) the volatility of various features of employment and (ii) the extent of AI use across different types of employment. We benefit from taking the most granular approach possible for measuring and matching both aspects for our analysis. Thus, we focus on labor market dynamics and AI use for specific occupations, rather than broad industries or sectors.

We adopt standard approaches for measuring the volatility of employment levels for detailed occupations observed between 1997 and 2024, as reported by the OEWS program at the BLS. First, we run a simple AR(1) regression on the employment growth rates (i.e., first differences) for each occupation, o. The absolute error terms $|\epsilon_{ot}^{FD}|$ from these regressions provide an unbiased estimate of the instantaneous volatility of employment for each occupation. We calculate the average absolute deviation in employment for each occupation over time, t, to measure the typical volatility in employment for each occupation, which we label σ_o^{FD}. Alternatively, we obtain detrended fluctuations in employment using an HP filter on annual employment levels for each occupation and then calculate the standard deviation of those detrended occupational employment fluctuations, σ_o^{HP}, to measure volatility.

Other measures of worker flows come from information in the CPS. We measure job-to-job transitions, job separations, job finding, and worker flows into and out of the labor force by capturing monthly changes in reported job statuses for workers in specific occupations. That is, we measure $E_o \rightarrow E$, $E_o \rightarrow U$, $U \rightarrow E_o$, $E_o \rightarrow O$, and $O \rightarrow E_o$ flows, respectively, from month to month for surveyed workers between 1997 and 2024, using the reported final weights for individual worker flows and log employment levels in 2024 for each occupation to aggregate to national measures of worker flows for each occupation. We then divide by total contemporaneous occupational employment to obtain measures of the propensities for each flow to occur. Finally, we average the propensities across all months and years in the sample period to obtain the typical rate of the corresponding job or worker flow observed for each occupation, $Pr(\cdot \rightarrow \cdot)_o$. Note that job-to-job transitions are considered for the originating occupation held by workers, allowing such flows to go into any other occupation.

The basis of the measures of AI use for the U.S. labor market is the Anthropic Economic Index (AEI). They report the exposure jobs have to AI at the detailed occupational level. Their measures of AI exposure combine several aspects of AI use, including the applicability of AI to certain tasks as characterized by Eloundou et al. (2024), the actual usage of AI to accomplish certain tasks, that use being in workplace settings, the depth of delegation to AI tools versus users augmenting work performed by AI, and finally the relative importance of a certain task within the overall requirements for each occupation.

In sum, AEI reports measures of AI use for 739 distinct occupations that match to employment flows in the OEWS. The scores for each occupation range from zero to one, with 401 occupations that having a score of zero and 338 with positive scores. Of those with positive measures of AI use, 75% of occupations exhibit scores that fall between 0 and 0.2. See Figure 1. We observe worker flows in the CPS for approximately 300 occupations that match to AEI metrics. Though this is significantly fewer than for the OEWS, the alternative markers in Figure 1 confirm that our sample reflects the population of observed AI use across occupations, rather than a selected set with high or low AI use.

The analysis in the following sections highlights the volatility of labor market outcomes between occupations that are not significantly exposed to AI and those that have some measured intensity of AI use; i.e., AI use$= 0$ versus AI use> 0. The AEI methodology to measure AI use in occupations, partially based on Eloundou et al. (2024), evaluates whether or not certain tasks can be accomplished in half of the typical time, which gives rise to the discrete nature of observed AI use. In an appendix we focus on finer subsamples that roughly divide occupations with positive AI use into four similarly sized groups (i.e., the quartiles for AI use > 0).[4] The results in the appendix confirm that the greater volatility in labor market outcomes is a feature of occupations for all levels of AI use and not driven by any outlying occupations with outsized applicability of AI technologies.

[Insert Figure 1 here]

Finally, we draw on previous work in Jorgenson et al. (2008), Carvalho and Gabaix (2013), and the Integrated Industry-Level Production Accounts (KLEMS) from the BEA to measure the volatility of aggregate output driven by productivity shocks within specific industries and changes in the concentrations of activities across industries. Together these data provide overlapping time spans that cover 1960-2024. Specifically, we replicate Carvalho and Gabaix (2013) to provide insights into production outcomes for 77 distinct SIC industries between 1960 and 2005 and supplement with BEA information for the years 1997-2024 for 61 NAICS sectors, excluding government sectors. Importantly, these data provide information about gross sales from each sector, not just value added, so that we can aggregate the industry-specific volatility up to the fundamental volatility of the U.S. economy in away that accounts for complementarities in production. We define IT-producing sectors consistent with Jorgenson et al. (2008) and AI-producing sectors as the Information & Data Processing Services (NAICS 518-19) and the Miscellaneous Professional, Scientific & Technical Services (NAICS 5412-14, 5416-19) sectors.

[4] Specifically, when looking at subsamples of occupations with positive AI exposure we consider those with AI exposure$= 0$, in the range $(0, 0.04]$, in the range $(0.04, 0.08]$, $(0.08, 0.20]$ and those occupations with AI exposure above 0.20.

4 Labor Market Volatility and AI Use

This section demonstrates how the volatility of various outcomes in the U.S. labor market are related to the use of AI across occupations. Altogether, these facts motivate the characterization of current AI technologies as being volatility-biased.

4.1 Employment levels over the business cycle

Figure 2 illustrates the skewness of AI-based technological change toward jobs that historically tend to exhibit more volatility in their employment levels over the business cycle. Specifically, Figure 2 plots the densities of estimated employment volatility measures for 739 occupations with different exposures to AI-based technological change: Panel A contrasts the distributions of employment volatility measured according to σ_o^{FD} for those occupations with some AI use (in orange) and those with AI use scores of zero (in yellow), weighted according to (log) employment levels observed in 2024; Panel B similarly contrasts observed employment volatility measured by σ_o^{HP}. The densities are estimated with an Epanechinikov kernel. In this context, the volatility-biased nature of AI-based technological change is indicated by the rightward skew in the density plots toward higher employment volatility for occupations more exposed to AI.[5]

[Insert Figure 2 here]

Occupations without significant AI use exhibit a strong tendency to have low volatility in employment outcomes from year to year, as indicated by the high density of jobs with low σ_o in the yellow distributions shown in Figure 2. Some occupations where AI technologies are used intensively do have low volatility, but many more exhibit higher values of σ_o, as

[5] The methodologies to estimate employment volatility involve absolute or squared deviations in employment levels; i.e., absolute or squared values of normally distributed shocks. These methodologies lead to strictly positive χ distributions. Thus, higher volatility among one subsample of occupations will appear as a further rightward skew. Regardless, we report Anderson-Darling statistics to evaluate the statistical significance of differences in the distributions of observed volatility, which are non-parametric and do not rely on distributional assumptions.

shown in orange. Occupations where AI-based technology is applied exhibit approximately 15.5% greater volatility on average based on the high-frequency measure of volatility, σ_o^{FD}, while the average cyclical volatility of employment away from trend measured by σ_o^{HP} is roughly 22.5% higher for occupations using AI. These differences are both sizable, and the disparity across volatility metrics, σ_o^{FD} and σ_o^{HP}, likely reflects the different frequencies of shocks being measured by each methodology. The estimated distributions of occupational employment volatility are significantly different at high degrees of statistical significance (Anderson-Darling statistics$=$ 4.56 and $=$ 6.089, $p-value < 0.01$ and $p-value < 0.001$ for σ_o^{FD} and σ_o^{HP}, respectively.) Qualitatively and quantitatively similar differences arise when considering unweighted volatility measures across occupations and among the sets of occupations with more finely measured differences in observed AI use. See the appendix.

4.2 Job-to-job transitions

The propensity for workers to switch jobs varies significantly across different occupations. Figure 3 shows the likelihood that workers switch jobs is historically higher for workers employed in occupations that exhibit greater use of current AI technologies. Specifically Figure 3 plots the densities of job-to-job transition rates observed across 315 occupations with different exposures to AI. The densities are estimated with an Epanechinikov kernel. In this context, the volatility-biased nature of AI-based technological change is indicated by the rightward shift in the density plots toward higher job-to-job transition rates for occupations more exposed to AI.

[Insert Figure 3 here]

The average job-to-job transition rate for workers in occupations using AI is almost 5% higher than for those employed in occupations not using AI intensively. The estimated distributions of job switching rates are significantly different at high degrees of statistical significance (Anderson-Darling statistic $= 7.323$, $p-value < 0.001$). Job switching behavior is a key labor market dynamic that varies over the business cycle and has strong associations with individual wage growth. These characteristics make the differences in observed job-to-job transition rates across occupations a prominent feature of labor market dynamics that differs by AI use.

4.3 Job finding rates

The frequency with which non-employed workers find a job varies widely across occupations. These job finding rates also differ depending on if workers were previously unemployed ($U \rightarrow E_o$) or previously out of the labor force ($O \rightarrow E_o$). Figure 4 shows that occupations with greater AI use are also those occupations with higher job finding rates among non-employed workers historically. Panel A contrasts the job finding rates among previously unemployed workers for occupations with greater AI use (in orange) and those with no significant use (in yellow), while Panel B contrasts job finding rates among workers who were previously not in the labor force. Again, the volatility-biased nature of AI-based technological change is indicated by the rightward shift in the density plots of observed job finding rates.

[Insert Figure 4 here]

The historical average of job finding rates for workers in occupations now using AI is approximately 15.4% higher among unemployed workers and 7.1% higher for those not in the labor force, each compared to occupations not using AI intensively. The estimated distributions of job switching rates are significantly different at reasonable degrees of statistical significance (Anderson-Darling statistics = 2.908 and = 3.353, $p - value < 0.05$, $p - value < 0.05$ for ($U \rightarrow E_o$) and ($O \rightarrow E_o$) flows, respectively). These results point to faster hiring outcomes in expansion periods on average for jobs amenable to current AI technologies.

4.4 Job loss and labor force participation

The behavior of workers after separating from a job is a key feature of business cycle volatility. Some workers exit the labor force rather than begin searching for a new job, and this propensity for workers to move to the sidelines, which we observe as a $E_o \rightarrow O$ flows, varies across occupations. Figure 5 shows the historical rate of transition out of the labor force from employment is starkly lower if workers were in jobs that are now exposed to AI, further demonstrating the orientation of current AI technologies toward labor market outcomes that exhibit greater dynamism. The propensity for workers to leave the labor force after losing a job exposed to AI is only 2/3 of that for jobs not exposed to AI. (Anderson-Darling statistics $= 14.141$, $p - value < 0.001$)

[Insert Figure 5 here]

5 Business Cycle Volatility and Technological Change

In this section, we demonstrate how the orientation of AI-based technological change toward the most volatile aspects of the U.S. economy influences the aggregate volatility of U.S. economic growth over time. The quantitative analysis closely follows Carvalho and Gabaix (2013), who derive a metric they call the fundamental volatility, σ_t^Y, that is the result of only microeconomic shocks that originate within sectors, and which closely tracks the observed volatility of aggregate U.S. output over time. They propose a straightforward multisector model of production in which individual sectors, $i = 1...N$, vary in the primitive volatility of their output due to total factor productivity shocks, σ_i, such that changes in the shares of economic activity across sectors, $\frac{S_{it}}{Y_t}$, over time lead to changes in the overall volatility of the U.S. economy. The S_{it} terms are gross sales terms (i.e., Domar weights) to allow for complementarity between sectors.[6] Given an aggregate Frisch elasticity of the labor supply,

[6] By focusing on gross sales, the terms S_{it} include sales to business within the same sector and to other sectors. This is a well-known and important feature of models of aggregate production that allow for complementarity, as demonstrated by Domar (1961), Hulten (1978) and many others since.

ψ, and labor share, α, a competitive equilibrium results in a fundamental volatility of output growth given by

$$\sigma_t^Y = \frac{1+\psi}{\alpha}\sqrt{\sum_{i=1}^{N}\left(\frac{S_{it}}{Y_t}\right)^2 \sigma_i^2}. \tag{1}$$

Figure 6 plots values of fundamental volatility from equation (1) as well as the observed volatility in U.S. GDP growth between 1960-2024. The observed volatility in output is measured as a 3-year moving average of the errors from an AR(1) regression of quarterly GDP growth, the dark blue line replicates the fundamental volatility measure reported in Carvalho and Gabaix (2013) for 1960-2009, and the green line extends their measure of fundamental volatility using information from the BEA from 1997-2024. The movements in σ_t^Y closely track observed GDP volatility historically, including longer term movements across decades as well as fluctuations at business cycle frequencies lasting a few years. The close connection between the fundamental volatility metric and observed GDP volatility motivate the use of equation (1) to examine the role of individual sectors in driving overall volatility of U.S. output. The long history in the fundamental volatility metric also facilitates comparison to previous episodes when aggregate volatility shifted, including another period of technological change that occurred during the IT-boom of the late 1990s.

Equation (1) specifies how shifts in the microfoundations of economic activity across sectors with differing volatility can lead to changes in the aggregate volatility of the U.S. economy. First, shifts in economic activity toward specific sectors (i.e., higher S_{it}/Y_t) that exhibit greater volatility, (i.e., higher σ_i) will directly raise the fundamental volatility of U.S. GDP. Second, increases in the aggregate elasticity of labor supply, ψ, would amplify the aggregate volatility of U.S. output resulting from sector-specific shocks. Third, the current AI boom is occurring during a period of significant decline in the labor share of income, α. This decline in α can further amplify changes in volatility that result from reallocations of economic activity toward high volatility sectors and changes in the elasticity of labor supply.

5.1 Volatility in AI-producing sectors

The production of AI-based technologies is largely concentrated in the Information & Data Processing Services sector (NAICS 323) and the Miscellaneous Professional, Scientific & Technical Services sector (NAICS 5412-14, 5416-19). The top section of Table 1 shows these sectors had Domar weights that were significantly larger than that of the median sector in 2024. They also exhibit ratios of gross sales to GDP that are roughly 50% larger than their ratios of value added to GDP. In other words, AI-producing sectors make relatively larger contributions to aggregate volatility due to complementarities they have with other production sectors. These facts are consistent with the nature of AI being "broad-based" technological change. Moreover, AI-producing sectors have grown in prominence in recent years. The bottom section of Table 1 shows that the ratio of gross sales to GDP increased by 0.77 percentage points for the data processing sector and by 0.39 percentage points in the miscellaneous professional, scientific & technical services sector between 2019 and 2024.

The key AI producing sector, Information & Data Processing Services, exhibits significantly greater volatility than most other sectors; the standard deviation of TFP growth, σ_i, is 11.2. This value is more than three times that of the median sector and roughly twice the volatility of any other sector except for the Commodity Contracts, & Investments sector and oil and gas related activities. As a result, Information & Data Processing Services alone accounted for 12.2% of the measured fundamental volatility underlying U.S. output in 2024. These facts about AI-producing sectors complement the volatility-biased nature of this new technology we see in the U.S. labor market.

The IT boom of the late 1990s was concentrated in sectors that exhibited moderate volatility compared to the AI boom. Yet, IT sectors made comparable contributions to fundamental volatility in 2000 that we observe for AI in 2024 due the integration of IT technologies across the U.S. economy, indicated by their large Domar weights. Given the higher volatility of AI-producing sectors and the potential for the technology to integrate further in the U.S. economy, AI could continue to play a role in driving underlying volatility.

5.2 AI-Technology Induced Changes in Aggregate Volatility

The last column in the bottom section of Table 1 reports the shares of the total change in volatility between 2019 and 2024 that are driven by the rising concentration of activity in high-volatility, AI-producing sectors. Specifically, these changes in the contribution to aggregate volatility are measured as $\frac{\Delta(S_{it}/Y_t)^2}{\Delta\sigma_Y^2}\sigma_i^2$. The shift in activity toward the high-volatility Data Processing sector not only raised aggregate volatility, but was large enough to slightly exceed the total increase in the fundamental volatility of output between 2019 and 2024. The only other sector to make a significant contribution to the recent rise in fundamental volatility was the Securities, Commodity Contracts, and Investments sector, which we recognize may contain AI-related financial investment activity. The rise in volatility from these financial linkages to AI-based technological change is another channel for technological change to influence aggregate volatility that we do not attempt to measure here. The increase in volatility resulting from the AI boom is larger than the IT boom largely because growth during the late 1990s was concentrated in relatively lower volatility IT sectors.

Shifts in fundamental volatility that originate from microeconomic foundations have been relatively modest in recent history compared with past decades, as seen in Figure 1. To put the current episode in context, the rise in aggregate volatility resulting from AI-producing industries is approximately 1/5 the size of the decline in volatility due to reductions in certain manufacturing activities between 1960 and 1990 or 1/4 the size of the increase in volatility resulting from an increase in oil & gas activities in the latter half of the 1970s. Though the ongoing AI-based technological change is the most prominent driver of volatility originating from microeconomic shocks currently, its consequences are still relatively modest from a historical perspective.

The potential for aggregate volatility to shift by greater magnitudes could depend on labor market channels related to AI use that amplify the effects of shocks related to the production of AI technologies. As in Carvalho and Gabaix (2013), we take the aggregate Frish elasticity, ψ, to encompass changes in hours worked per person, changes in effort, and changes in employment across the business cycle. In other words, there are several labor market outcomes that could each influence the aggregate labor supply elasticity. Given the range of outcomes that exhibit significantly higher volatility among occupations using AI described in Section 4, there are also several avenues for the aggregate labor supply elasticity to rise as a result of technological change. The evidence presented in Jaimovich and Siu (2009), and confirmed in Carvalho and Gabaix (2013), demonstrates that the labor supply elasticity, ψ, does indeed vary over long time horizons as the demographic composition of the labor force shifts and exhibits different degrees of dynamism. Greater volatility in employment outcomes, job switching behavior, and different searching behavior across occupations has the potential to raise the aggregate labor supply elasticity over relatively shorter time horizons.

Similarly, the labor share for the U.S. economy, α, has been declining from its historical average in recent years. This could serve to amplify the effects of sector-specific shocks on aggregate volatility if greater capital intensity in production were to expedite the reallocation of activity across sectors. It is perhaps too soon to tell how important this effect will be, however it is notable that the labor share is declining during the current AI boom while it was rising by approximately the same amount during the IT boom.

6 Conclusion

Policymakers are currently facing a challenge of understanding how the ongoing technological change of the AI boom is influencing overall economic growth, productivity, investment activity, and labor market outcomes, among others issues. The focus on the current transitional aspects of this new technology is certainly warranted given its pervasiveness and the speed of its adoption. However, monetary policy and many fiscal policy tools are meant to manage ebbs and flows in economic activity over the business cycle. The results reported here regarding volatility highlight considerations about this new technology that policymakers may need to take into account over the long term.

References

Daron Acemoglu. Technical change, inequality, and the labor market. *Journal of Economic Literature*, 40 (1):7–72, March 2002. doi: 10.1257/0022051026976. URL https://www.aeaweb.org/articles?id=10.1257/0022051026976.

Daron Acemoglu, David Autor, Jonathon Hazell, and Pascual Restrepo. Artificial Intelligence and Jobs: Evidence from Online Vacancies. *Journal of Labor Economics*, 40(S1):S293–S340, April 2022. ISSN 0734-306X, 1537-5307. doi: 10.1086/718327. URL https://www.journals.uchicago.edu/doi/10.1086/718327.

Jonathan J. Adams, Min Fang, Zheng Liu, and Yajie Wang. The rise of AI pricing: Trends, driving forces, and implications for firm performance. *Journal of Monetary Economics*, 157:103875, January 2026. ISSN 03043932. doi: 10.1016/j.jmoneco.2025.103875. URL https://linkinghub.elsevier.com/retrieve/pii/S0304393225001461.

David H. Autor, Frank Levy, and Richard J. Murnane. The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333, 11 2003. ISSN 0033-5533. doi: 10.1162/003355303322552801. URL https://doi.org/10.1162/003355303322552801.

Andrew B. Bernard and Charles I. Jones. Technology and convergence. *The Economic Journal*, 106(437): 1037–1044, 07 1996. ISSN 0013-0133. doi: 10.2307/2235376. URL https://doi.org/10.2307/2235376.

Jeff E. Biddle. Making Consumers Comfortable: The Early Decades of Air Conditioning in the United States. *The Journal of Economic History*, 71(4):1078–1094, December 2011. ISSN 0022-0507, 1471-6372. doi: 10.1017/S0022050711002257. URL https://www.cambridge.org/core/product/identifier/S0022050711002257/type/journal_article.

Olivier (Olivier J.) Blanchard and John Simon. The Long and Large Decline in U.S. Output Volatility. *Brookings Papers on Economic Activity*, 2001(1):135–174, 2001. ISSN 1533-4465. doi: 10.1353/eca.2001.0013. URL https://muse.jhu.edu/article/10347.

Vasco Carvalho and Xavier Gabaix. The Great Diversification and its Undoing. *American Economic Review*, 103(5):1697–1727, August 2013. ISSN 0002-8282. doi: 10.1257/aer.103.5.1697. URL https://pubs.aeaweb.org/doi/10.1257/aer.103.5.1697.

Richard Clarida, Jordi Gali, and Mark Gertler. Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory*. *Quarterly Journal of Economics*, 115(1):147–180, February 2000. ISSN 0033-5533, 1531-4650. doi: 10.1162/003355300554692. URL https://academic.oup.com/qje/article-lookup/doi/10.1162/003355300554692.

Evsey D. Domar. On the measurement of technological change. *The Economic Journal*, 71(284):709–729, 12 1961. ISSN 0013-0133. doi: 10.2307/2228246. URL https://doi.org/10.2307/2228246.

G. Duranton, P. M. Morrow, and M. A. Turner. Roads and Trade: Evidence from the US. *The Review of Economic Studies*, 81(2):681–724, April 2014. ISSN 0034-6527, 1467-937X. doi: 10.1093/restud/rdt039. URL https://academic.oup.com/restud/article-lookup/doi/10.1093/restud/rdt039.

Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock. GPTs are GPTs: Labor market impact potential of LLMs. *Science*, 384(6702):1306–1308, June 2024. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.adj0998. URL https://www.science.org/doi/10.1126/science.adj0998.

R. Jason Faberman. Job flows, jobless recoveries, and the Great Moderation. *Journal of Economic Dynamics and Control*, 76:152–170, March 2017. ISSN 01651889. doi: 10.1016/j.jedc.2017.01.006. URL https://linkinghub.elsevier.com/retrieve/pii/S0165188917300143.

Edward Felten, Manav Raj, and Robert Channing Seamans. The Effect of Artificial Intelligence on Human Labor: An Ability-Based Approach. *Academy of Management Proceedings*, 2019(1):15784, August 2019. ISSN 0065-0668, 2151-6561. doi: 10.5465/AMBPP.2019.140. URL http://journals.aom.org/doi/10.5465/AMBPP.2019.140.

Xavier Gabaix. The Granular Origins of Aggregate Fluctuations. *Econometrica*, 79(3):733–772, 2011. ISSN 0012-9682. doi: 10.3982/ECTA8769. URL http://doi.wiley.com/10.3982/ECTA8769.

Gene Grossman and Esteban Rossi-Hansberg. The rise of offshoring: It's not wine for cloth anymore. *Economic Policy Symposium, Federal Reserve Bank of Kansas City*, The New Economic Geography: Effects and Policy Implications, 2006. URL www.kansascityfed.org/research/jackson-hole-economic-symposium/the-new-economic-geography-effects-and-policy-implications.

Charles R. Hulten. Growth accounting with intermediate inputs. *The Review of Economic Studies*, 45(3): 511–518, 10 1978. ISSN 0034-6527. doi: 10.2307/2297252. URL https://doi.org/10.2307/2297252.

Owen Irvine and Scott D. Schuh. The Roles of Comovement and Inventory Investment in the Reduction of Output Volatility. *SSRN Electronic Journal*, 2005. ISSN 1556-5068. doi: 10.2139/ssrn.770324. URL http://www.ssrn.com/abstract=770324.

Nir Jaimovich and Henry E Siu. The Young, the Old, and the Restless: Demographics and Business Cycle Volatility. *American Economic Review*, 99(3):804–826, May 2009. ISSN 0002-8282. doi: 10.1257/aer.99.3.804. URL https://pubs.aeaweb.org/doi/10.1257/aer.99.3.804.

Dale W Jorgenson, Mun S Ho, and Kevin J Stiroh. A Retrospective Look at the U.S. Productivity Growth Resurgence. *Journal of Economic Perspectives*, 22(1):3–24, February 2008. ISSN 0895-3309. doi: 10.1257/jep.22.1.3. URL https://pubs.aeaweb.org/doi/10.1257/jep.22.1.3.

Aakash Kalyani, Nicholas Bloom, Marcela Carvalho, Tarek Hassan, Josh Lerner, and Ahmed Tahoun. The Diffusion of New Technologies. *The Quarterly Journal of Economics*, 140(2):1299–1365, April 2025. ISSN 0033-5533, 1531-4650. doi: 10.1093/qje/qjaf002. URL https://academic.oup.com/qje/article/140/2/1299/7959830.

Miklós Koren and Silvana Tenreyro. Volatility and development. *The Quarterly Journal of Economics*, 122 (1):243–287, 02 2007. ISSN 0033-5533. doi: 10.1162/qjec.122.1.243. URL https://doi.org/10.1162/qjec.122.1.243.

Subodh Kumar and R. Robert Russell. Technological Change, Technological Catch-up, and Capital Deepening: Relative Contributions to Growth and Convergence. *American Economic Review*, 92(3):527–548, May 2002. ISSN 0002-8282. doi: 10.1257/00028280260136381. URL https://pubs.aeaweb.org/doi/10.1257/00028280260136381.

Margaret M McConnell and Gabriel Perez-Quiros. Output Fluctuations in the United States: What Has Changed Since the Early 1980's? *American Economic Review*, 90(5):1464–1476, December 2000. ISSN 0002-8282. doi: 10.1257/aer.90.5.1464. URL https://pubs.aeaweb.org/doi/10.1257/aer.90.5.1464.

Benjamin Wild Pugsley and Ayşegül Şahin. Grown-up Business Cycles. *The Review of Financial Studies*, 32(3):1102–1147, March 2019. ISSN 0893-9454, 1465-7368. doi: 10.1093/rfs/hhy063. URL https://academic.oup.com/rfs/article/32/3/1102/5034938.

Danny T. Quah. Twin Peaks: Growth and Convergence in Models of Distribution Dynamics. *The Economic Journal*, 106(437):1045, July 1996. ISSN 00130133. doi: 10.2307/2235377. URL https://academic.oup.com/ej/article/106/437/1045-1055/5159156.

James H. Stock and Mark W. Watson. Has the Business Cycle Changed and Why? *NBER Macroeconomics Annual*, 17:159–218, January 2002. ISSN 0889-3365, 1537-2642. doi: 10.1086/ma.17.3585284. URL https://www.journals.uchicago.edu/doi/10.1086/ma.17.3585284.

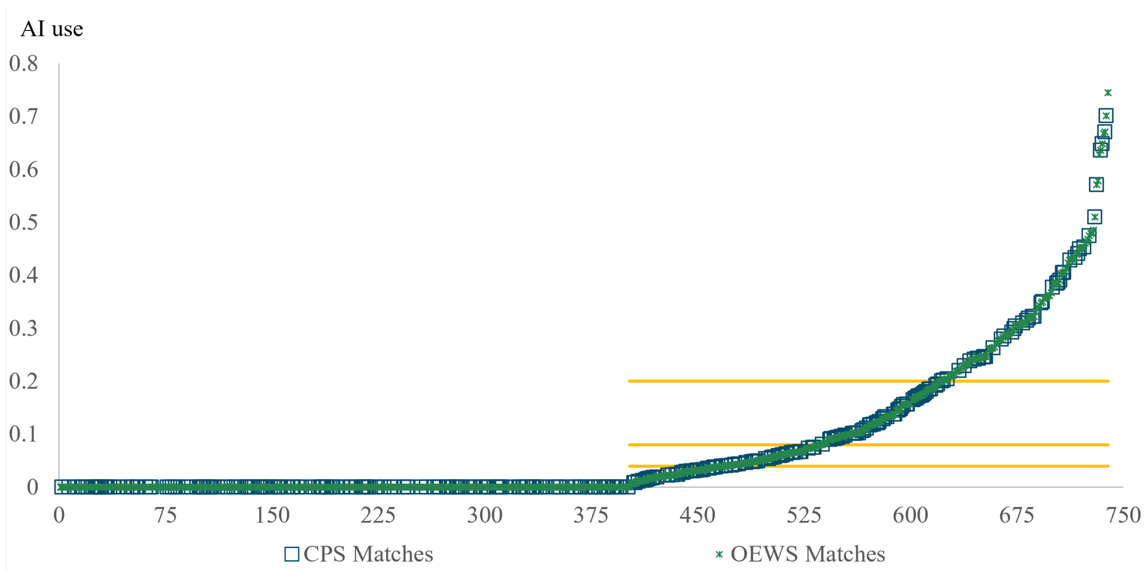
Michael Webb. The Impact of Artificial Intelligence on the Labor Market. *SSRN Electronic Journal*, 2019. ISSN 1556-5068. doi: 10.2139/ssrn.3482150. URL https://www.ssrn.com/abstract=3482150.

Table 1: Changes in Fundamental Volatility of U.S. Output Due to Technological Change

	Ind. Volatility	Domar Weight		Agg. Vol. Share	
Empirical Baselines	(σ_i)	$\left(\frac{S_{it}}{Y_t}\right)$		$\left(\frac{S_{it}}{Y_t}\frac{\sigma_i}{\sigma_Y}\right)^2$	
		2000	2024	2000	2024
Computer & electronic prod.	5.28	5.43	1.37	8.28	0.58
Broadcasting and telecomm.	3.65	5.30	3.00	3.77	1.33
Computer sys. design & svcs.	2.51	2.07	2.42	0.27	0.41
Misc. prof. & tech. svcs.	2.11	6.67	7.55	1.99	2.81
Info. & data processing svcs.	11.2	0.69	2.96	0.61	12.2
Median Sector	3.38	1.62	1.46	0.33	0.27
Empirical Changes		$\left(\Delta\frac{S_{it}}{Y_t}\right)$		$\left(\frac{\Delta(S_{it}/Y_t)^2}{\Delta\sigma_Y^2}\sigma_i^2\right)$	
		1997-2000	2019-'24	1997-2000	2019-'24
Computer & electronic prod.	–	0.02	-0.30	0.42	-5.71
Broadcasting and telecomm	–	0.81	-0.89	7.37	-18.4
Computer sys. design & svcs.	–	0.63	0.02	0.96	0.13
Misc. prof. & tech. svcs.	–	0.58	0.39	2.30	5.84
Info. & data processing svcs.	–	0.16	0.77	1.69	111.9

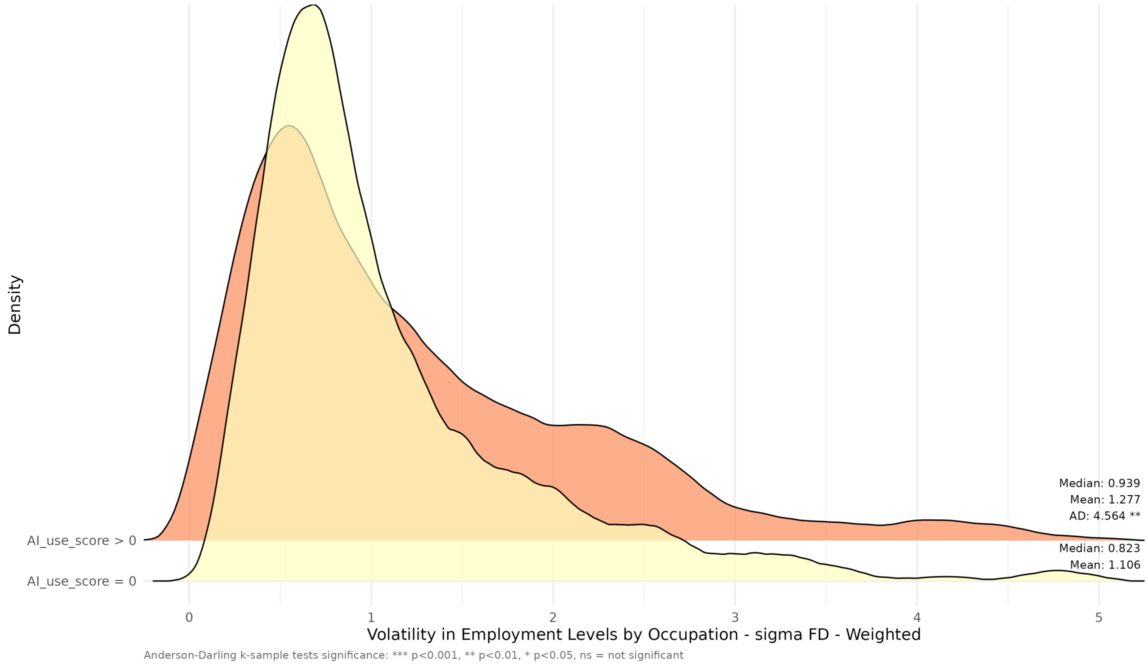
Note: Authors' calculations based on data from BEA Integrated Industry Accounts for 1997-2024. The values of the Domar Weights and Aggregate Volatility Shares are presented as percentage points.

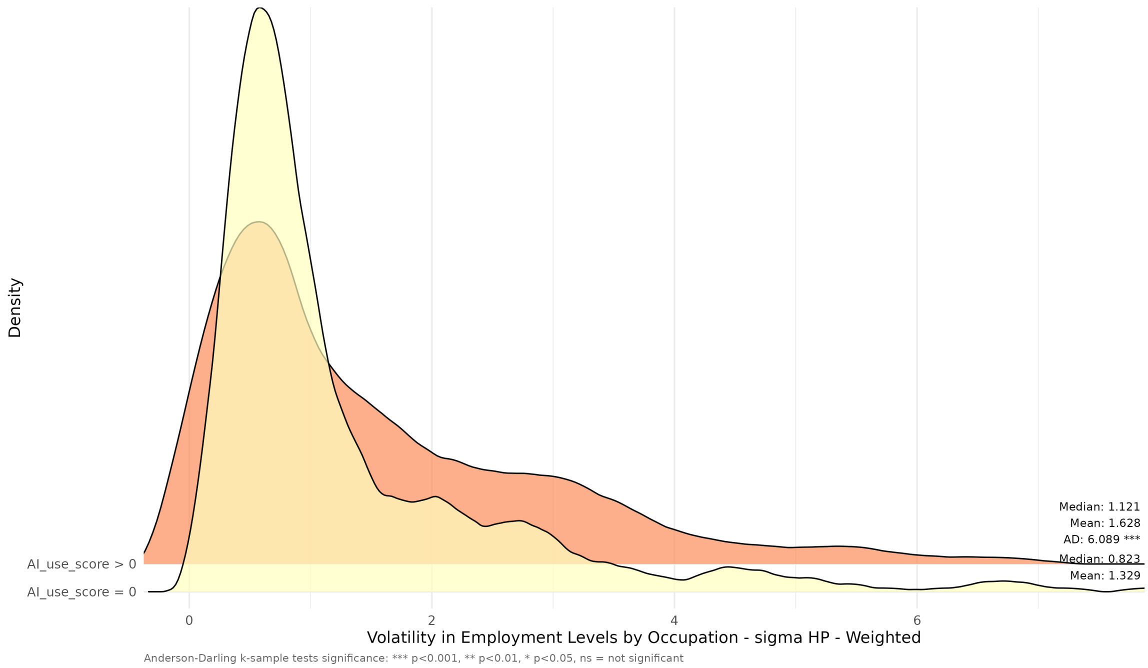
Figure 1: Observed AI Use Scores Across Occupations, Ordered by Rank



Notes: These data are reported by the Anthropic Economic Index and matched to occupations observed in the OEWS and CPS by the authors. The horizontal orange lines indicate the quartile range cutoffs for occupations with positive AI use scores, which are (0, 0.04], in the range (0.04, 0.08], (0.08, 0.20] and those occupations with AI use scores above 0.20.

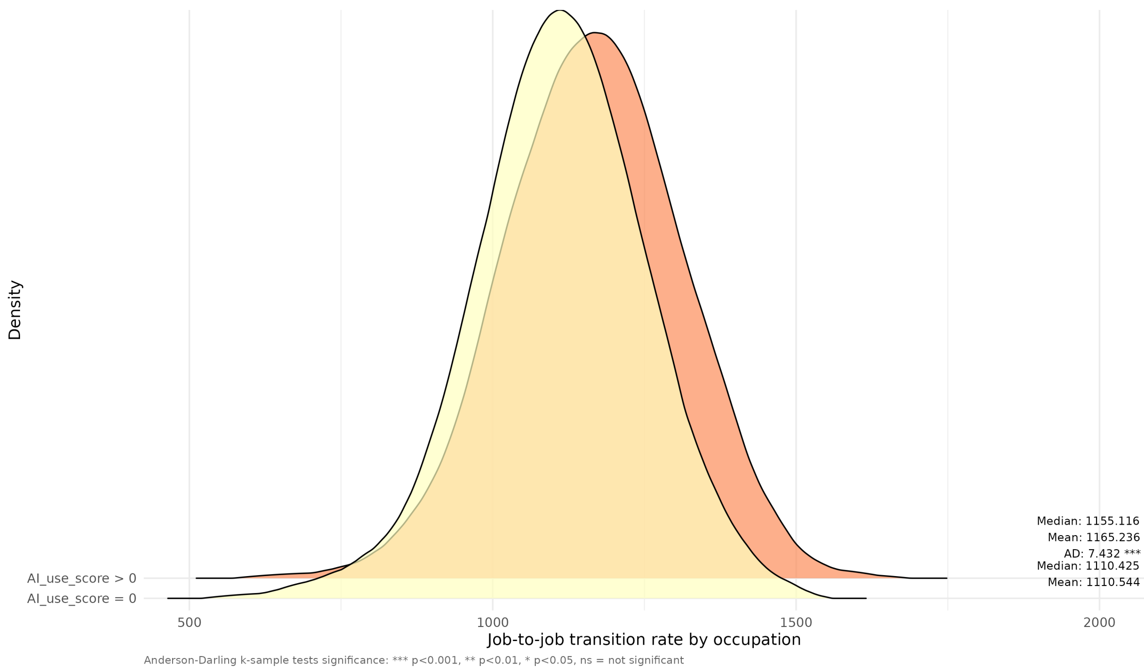
Figure 2: Employment Volatility Across Occupations According to AI Use





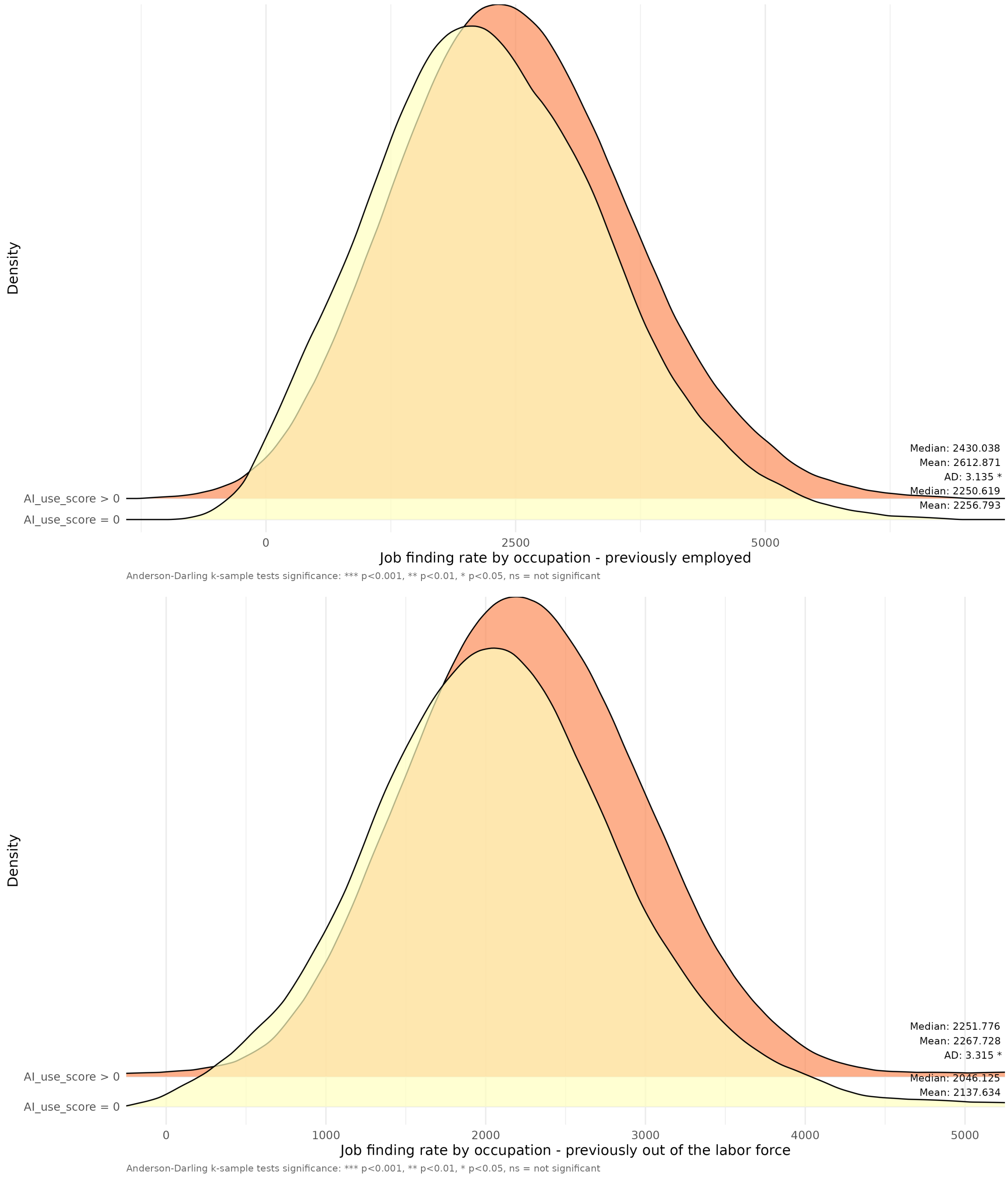
Notes: Authors' calculations based on BLS reports of Occupational Employment and Wage Statistics. Panel A shows the densities of employment volatility across occupations measured according to the first difference methodology, σ_o^{FD}, while Panel B shows occupational employment volatility measured after extracting HP trends, σ_o^{HP}. Each occupational employment volatility measure is weighted according to the observed employment level (log) in 2024. Occupations with AI use scores of zero shown in yellow and occupations with positive AI use scores shown in orange. The densities are estimated with an Epanechinikov kernel.

Figure 3: Job Switching Across Occupations According to AI Use



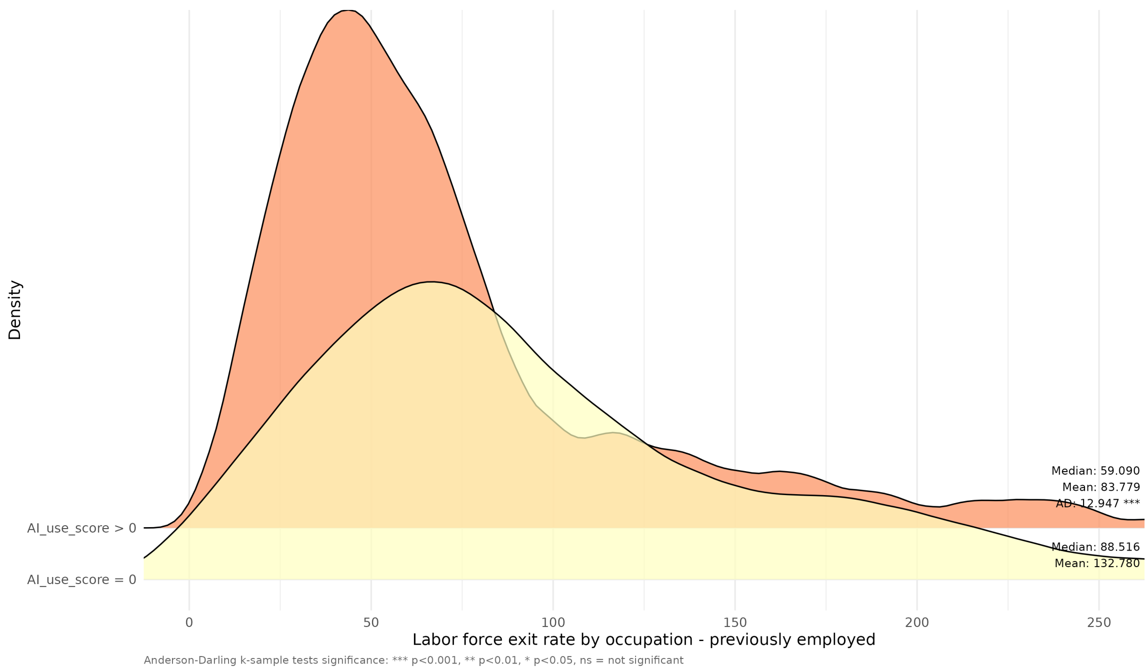
Notes: Authors' calculations based on CPS reports. The figure shows the job-to-job transition rates across occupations delineated according to AI exposure. Occupations with AI use scores shown in yellow and occupations with positive AI use scores shown in orange. Each occupational job switching rate is weighted according to the observed employment level (log) in 2024. The densities are estimated with an Epanechinikov kernel.

Figure 4: Job Finding Rates Across Occupations According to AI Use



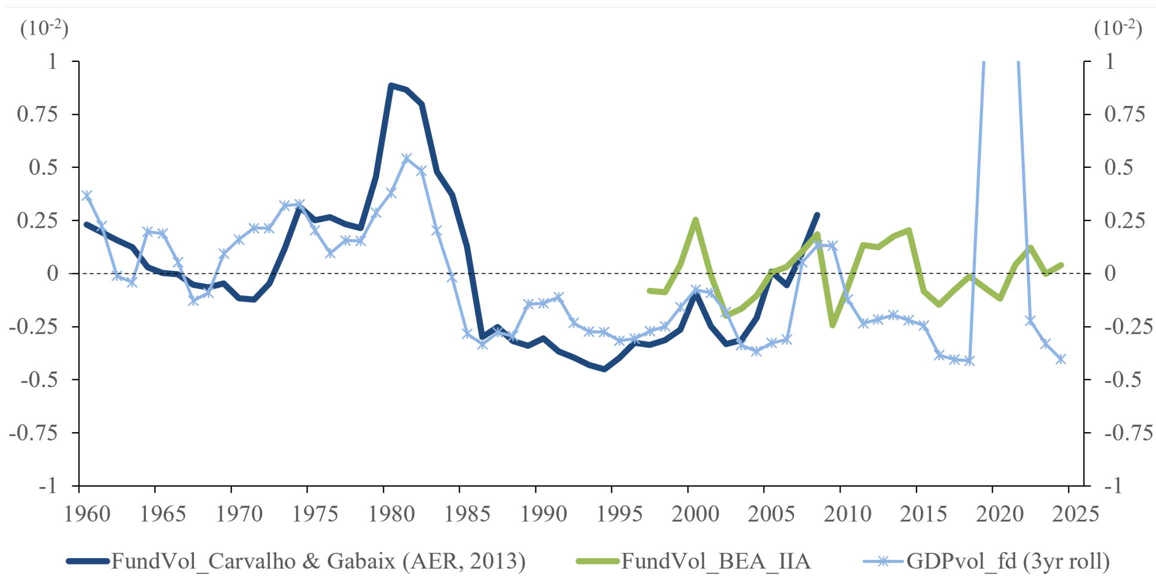
Notes: Authors' calculations based on CPS reports. Panel A shows rates of flows from unemployment to employment across occupations, while Panel B show the rates of flows for workers out of the labor force to employment, each delineated according to AI exposure. Occupations with AI use scores of zero shown in yellow and occupations with positive AI use scores shown in orange. Each observation is weighted according to the observed employment level (log) in 2024. The densities are estimated with an Epanechinikov kernel.

Figure 5: Labor Force Exits Following Job Losses Across Occupations According to AI Use



Notes: Authors' calculations based on CPS reports. The figure shows labor force exit rates across occupations delineated according to AI exposure. Occupations with AI use scores of zero shown in yellow and occupations with positive AI use scores shown in orange. Each observation is weighted according to the observed employment level (log) in 2024. The densities are estimated with an Epanechinikov kernel.

Figure 6: Fundamental Volatility and Observed Volatility of U.S. Output

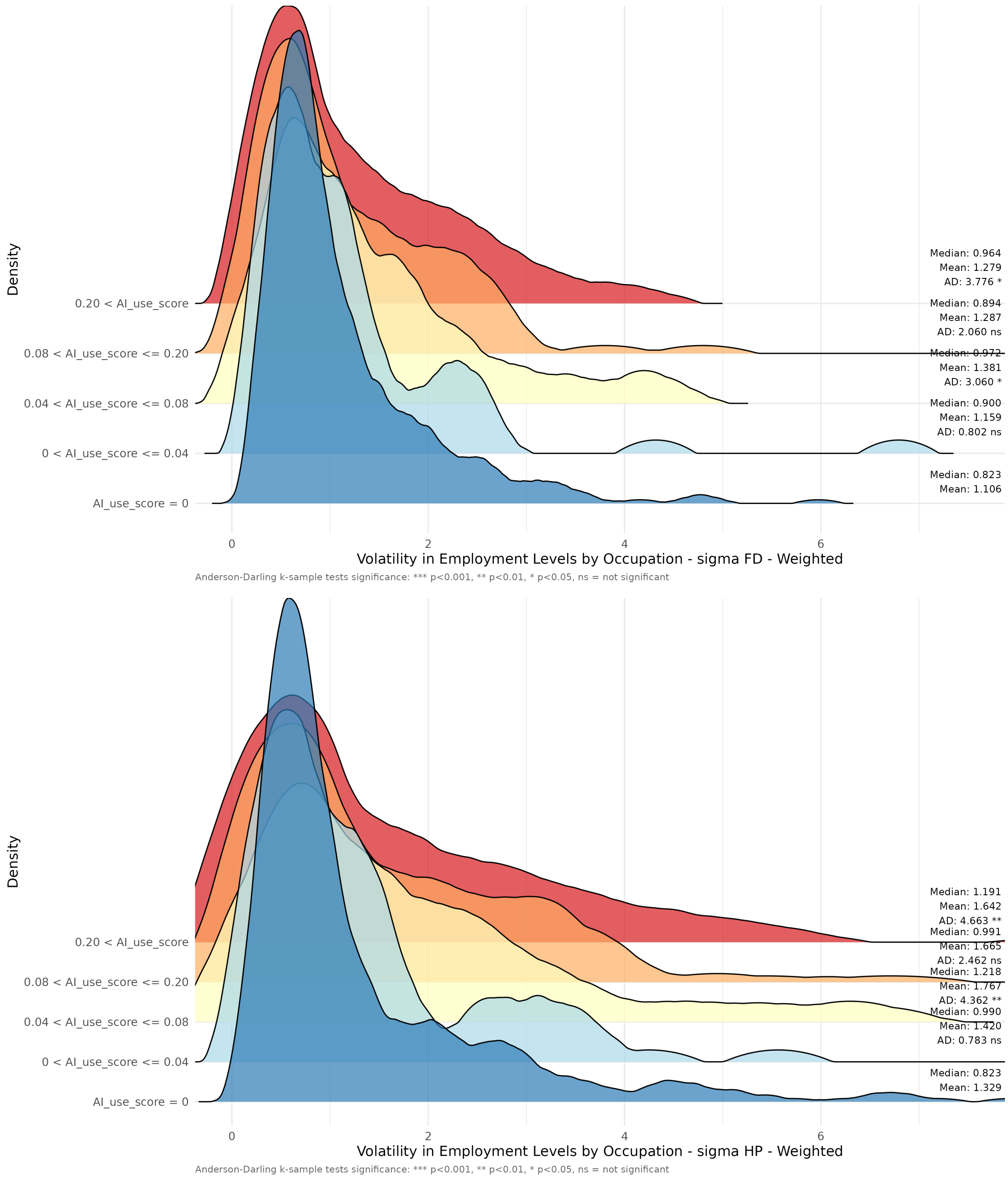


Notes: The starred line is the observed volatility in U.S. output, measured as a 3-year moving average of the errors from an AR(1) regression of quarterly GDP growth. The the dark blue line replicates the fundamental volatility measure reported in Carvalho and Gabaix (2013) for 1960-2009, and the green line extends their measure of fundamental volatility based on information from the BEA from 1997-2024 using authors' calculations. All values reported as deviations from series means.

Appendix

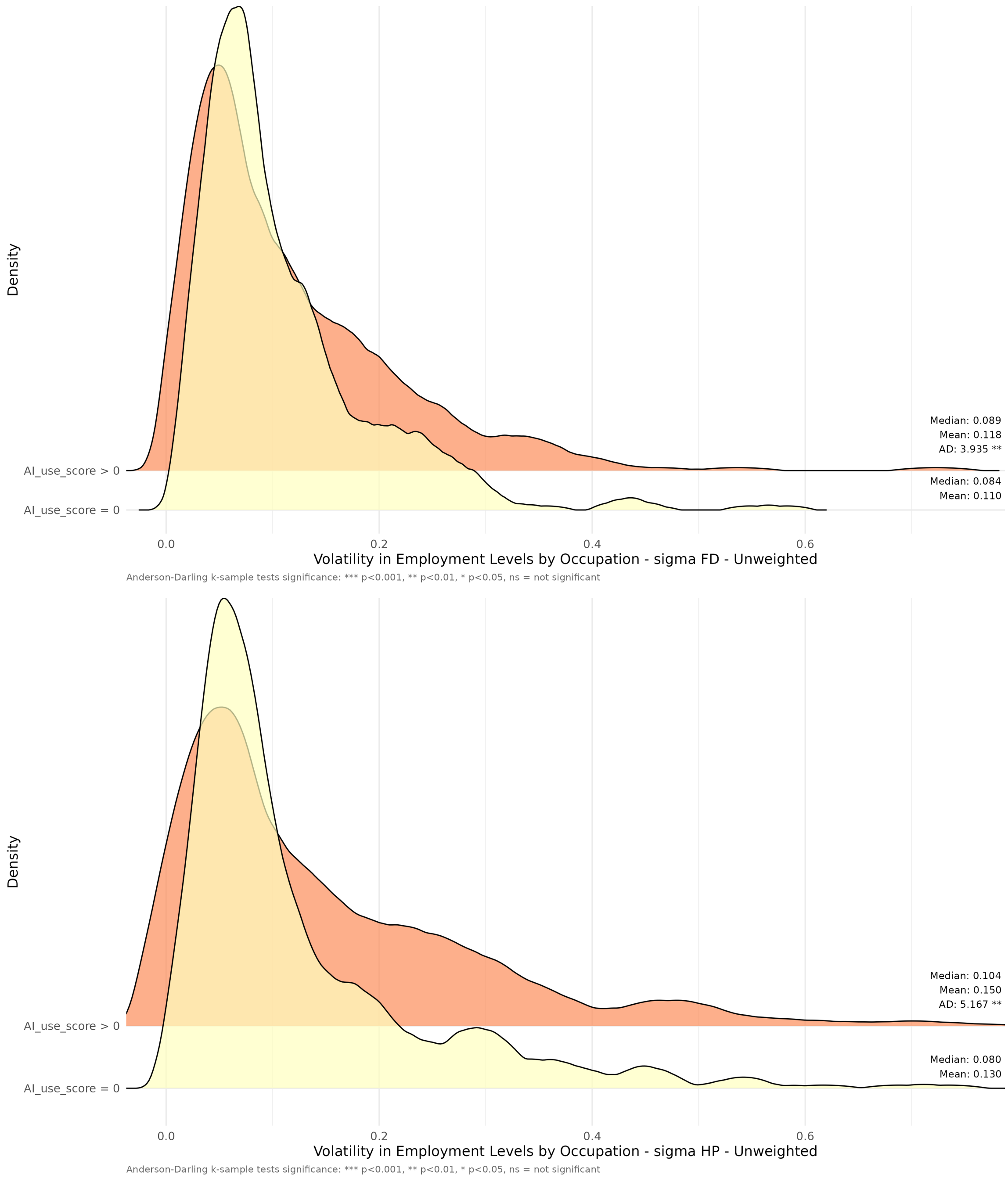
This appendix reports supplemental results to the main text. Specifically, we report differences in employment volatility across occupations with AI use scores that reflect the quartiles of positive scores rather than the bifurcated AI use$=0$ and AI use>0 to address concerns that outliers in AI use are driving results; we report differences in employment volatility across occupations according to AI use that are not weighted by (log) employment levels to address concerns that outliers of large occupation classifications were driving our results; and we report differences in employment volatility across occupations according to AI use observed in the full span of idiosyncratic deviations from trend in employment outcomes to address concerns that patterns of employment fluctuations may be asymmetric or otherwise exhibit patterns that make the mean absolute deviations or standard deviations in shocks reported in the main text poor indicators of overall volatility. For each alternative reported in this appendix, the results align closely with the main text.

Figure A1: Employment Volatility Across Occupations According to AI Use, Quartiles



Notes: Authors' calculations based on BLS reports of Occupational Employment and Wage Statistics. AI use scores correspond to zero, and the quartile cutoffs of AI positive use scores, which are (0, 0.04], in the range (0.04, 0.08], (0.08, 0.20] and those occupations with AI use scores above 0.20. Panel A shows the densities of employment volatility across occupations measured according to the first difference methodology, σ_o^{FD}, while Panel B shows occupational employment volatility measured after extracting HP trends, σ_o^{HP}. Each occupational employment volatility measure is weighted according to the observed employment level (log) in 2024. The densities are estimated with an Epanechinikov kernel.

Figure A2: Employment Volatility Across Occupations According to AI Use, Unweighted



Notes: Authors' calculations based on BLS reports of Occupational Employment and Wage Statistics. Panel A shows the densities of employment volatility across occupations measured according to the first difference methodology, σ_o^{FD}, while Panel B shows occupational employment volatility measured after extracting HP trends, σ_o^{HP}. As an alternative to the main text, here each occupational employment volatility measure is not weighted according to the observed employment level (log) in 2024. Occupations with AI use scores of zero shown in yellow and occupations with positive AI use scores shown in orange. The densities are estimated with an Epanechinikov kernel.

Figure A3: Employment Volatility Across Occupations According to AI Use, Idiosyncratic Shocks

Notes: Authors' calculations based on BLS reports of Occupational Employment and Wage Statistics. Panel A shows the densities of employment volatility indicated by the idiosyncratic deviations obtained from the AR(1) on first difference of annual occupational employment growth between 1997 and 2024 (rather than the mean absolute deviation reported in the text), while Panel B shows occupational employment volatility measured as the idiosyncratic deviations from the HP trend (rather than the standard deviation of these shocks). Each occupational employment volatility measure is weighted according to the observed employment level (log) in 2024. Occupations with AI use scores of zero shown in yellow and occupations with positive AI use scores shown in orange. The densities are estimated with an Epanechinikov kernel.