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Income dynamics in the United Kingdom and the impact of the Covid-19 recession

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In this paper, we use an employer-based survey of earnings and hours to set out the key patterns in UK earnings dynamics from 1975 to 2020, with a particular focus on the most recent recession. We demonstrate that (log) earnings changes exhibit strongly procyclical skewness and have become increasingly leptokurtic, and thus less well approximated by a log-normal distribution, over the period of study. This holds across genders and sectors. Exploiting the long duration of our panel, we then explore the responsiveness of earnings and hours to aggregate and firm-level shocks, finding ample heterogeneity in the exposure of different types of workers to aggregate shocks. Exposure is falling in age, firm size, skill level, and permanent earnings, and is lower for unionized and public sector workers. The qualitative patterns of earnings changes across workers observed in the Covid-19 recession of 2020 are broadly as predicted using the previously estimated exposures and size of the shock. Firm-specific shocks are important for wages given the variation in within-firm productivity and the patterns of heterogeneity are markedly different than for aggregate shocks.

Keywords. Income Dynamics, Inequality, Wage Shocks.

JEL classification. J01, J30.

1. Introduction

The United Kingdom (UK) has been the subject of substantial academic study when it comes to inequality. The rise in earnings inequality over the period covered by this study

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has been well established in a multitude of studies with a wide array of data sets. With some notable exceptions, the topic of income dynamics has received significantly less attention. In this paper, we seek to plug this gap. We first present a battery of descriptive estimates for comparison with those of other countries in this special issue, before investigating the aggregate and firm components of income dynamics, with a special focus on the recent 2020 recession.[1]

Our period of study is extensive, stretching back 45 years from 2020. To understand the descriptive patterns of inequality, volatility, and mobility that we set out in the main text, in Appendix A of the Online Supplementary Material (Bell, Bloom, and Blundell (2022)), we provide an overview of the main labor market events of our period of study and discuss the relevant UK labor market institutions. These provide a backdrop to the key patterns shown in the main text, of rising earnings inequality and changes to earnings dynamics over time.[2] The key results from this section are first that the distribution of earnings dynamics has becoming increasingly leptokurtic (fatter tailed) over the study period. Second, the distribution of 1 and 5-year changes in earnings differ substantially by worker characteristics, in line with the patterns shown using administrative data in the US (Guvenen, Karahan, Ozkan, and Song (2021)). Third, when it comes to a worker's position in the earnings distribution, the older a worker gets the more fixed their position is. We find some evidence that 10-year mobility across the earnings distribution has fallen over time.

Following the broad investigation of inequality, volatility, and mobility, we narrow our focus onto the responsiveness of earnings and hours to aggregate and firm-level shocks. We estimate a contemporaneous aggregate earnings GDP beta of 0.38, meaning that a 1% increase in GDP is associated with a 0.38% increase in earnings. The earnings elasticity is close to 1 when wage inertia is accounted for by including lagged GDP effects. However, we provide evidence of strong asymmetries, with the contemporaneous elasticity rising to 0.73 in expansionary periods and falling close to zero in recessions. Leveraging data on hours, we find a relatively large hours response to GDP fluctuations, with an elasticity estimate of 0.16. Again, there are asymmetries, but these are in the opposite direction to earnings, with hours responses coming mostly from recessionary periods.

A unique aspect of our data is that it is updated frequently, meaning that it already includes earnings data for 2020. This allows us to provide some early evidence on the earnings response to the Covid recession. For administrative-quality earnings data, which is often associated with a significant time delay, this is unusual. Our core results suggest that both in aggregate and in cross-group comparisons, the earnings hit is close to what we would have predicted given the size of the shock and historically estimated earnings—GDP betas—in that sense, this time is not different.

[1]To be consistent with other papers in this special issue, we will often refer to earnings as "income," though the two are distinct. As described in the data section, "income" here refers to labor market earnings.

[2]All of the statistics contained in the paper, together with additional statistics calculated from the data are publicly available through the Global Repository of Income Dynamics (GRID) database, together with harmonized statistics for the other countries in this issue of *Quantitative Economics*.

Our earnings data can be matched to firm-level data to allow an analysis of the impact of firm-level shocks in value-added on earnings. Our results suggest such shocks have an important role for earnings given the substantial within-firm variation in the value-added observed. Since the variation in these firm-level shocks is an order of magnitude larger than for aggregate shocks, we find that earnings changes are driven more by firm-level than aggregate shocks. Interestingly, the patterns of exposure to firm-level shocks across workers of different types is markedly different to those for aggregate shocks, with higher-earning workers in larger firms more affected.

This article is structured as follows. In Section 2, we discuss the primary data sets used. In Section 3, we present a series of descriptive patterns in income inequality, volatility, and mobility. In Section 4, we first exploit the long time dimension of our data set to estimate the effect of aggregate economic shocks on workers' earnings and hours. We show that there is substantial heterogeneity across workers in their response to aggregate shocks and that the patterns are generally consistent with those found in the United States (Guvenen, Schulhofer-Wohl, Song, and Yogo (2017)). We also expand on the comparison of the Covid-19 shock and previous shocks. Finally, we report estimates of the impact of firm-level shocks on earnings before concluding in Section 5.

2. Data

2.1 *Annual survey of hours and earnings*

Our analysis requires data with detailed information on earnings and a long panel component. For the UK, the only available data set which meets these requirements is the Annual Survey of Hours and Earnings (ASHE), formerly named the New Earnings Survey (NES).[3] This is the premier source of earnings information in the UK and forms the basis for many official wage statistics. It is a 1% sample of all employees, with a panel structure, which makes it possible to follow workers over time. The study has been used extensively for research on inequality, and due to its detailed earnings information also for studies on wage rigidities (Nickell and Quintini (2003), Elsby, Shin, and Solon (2016)). Firm identifiers have also led it to be used for studies on the role of within and between-firm inequality (Schaefer and Singleton (2020)).

The panel data set is available back to 1975 and is administered by the Office for National Statistics (ONS). Workers enter the sample frame by having a particular pair of digits at the end of their National Insurance Number (NIN), the UK equivalent of a Social Security number, randomly assigned to all workers upon labor market entry. Surveyors then identify the employer(s) of these individuals by Her Majesty's Revenue and Customs (HMRC) Pay As You Earn (PAYE) system, the UK government's income tax withholding system. This takes place each January.

Survey forms are then sent to employers requesting information on the worker(s) in the sampling frame who are identified as working for that employer in the PAYE records.

[3] Office for National Statistics. (2020). Annual Survey of Hours and Earnings, 1997–2020: Secure Access. [data collection]. 17th Edition. UK Data Service. SN: 6689, http://doi.org/10.5255/UKDA-SN-6689-16. Office for National Statistics. (2017). New Earnings Survey Panel Dataset, 1975–2016: Secure Access. [data collection]. 7th Edition. UK Data Service. SN: 6706, http://doi.org/10.5255/UKDA-SN-6706-7.

It is a legal requirement for firms to complete the survey. Employers complete the forms using information from payroll records. For larger employers, much of the process is automated, with surveyors accessing payroll records and extracting information directly. The survey covers both the public and private sectors, and as it is administered via employers it excludes the self-employed, who constitute approximately 15% of UK employment as of 2019. The survey delivers useable information on 140,000 to 180,000 employees each year. Workers are followed throughout their entire working lives (as their NIN does not change), so years can be combined to form a panel data set. Further details of the data set and a comparison of inequality trends with other household survey data are provided in Appendix B of the Online Supplementary Material.

The variables consistently available throughout the entire period include detailed wage and hours information for a snapshot period in April. Wages are broken down into standard and overtime pay. Studies using ASHE tend to use either weekly or hourly wages. From 1998, ASHE also provides a measure of annual earnings over the previous April–April tax year. This variable refers only to annual earnings at the worker's current employer, and so needs to be used with caution as for workers who move employers this will cover only part of their annual salary. Wages in ASHE are not topcoded.

Our main outcome of interest is weekly earnings. Earnings include overtime pay and any bonuses related to the surveyed work week. Where useful, we produce statistics using annual earnings for comparison. Earnings are deflated by CPI and given in 2018 GBP unless otherwise noted. To retain anonymity, where percentiles or percentile-based statistics are reported, data are binned into groups of 10 individuals and each individual is then assigned the group mean.

For Section 3 of this paper in which we inspect trends in inequality, volatility, and mobility, we restrict our analysis to workers aged 25–55. As is standard when using ASHE data, we exclude those whose pay is affected by absence in the reference week. Some papers using this data exclude those on training/apprenticeship wages. In practice, the age restriction means that this applies to very few workers in our sample, and irrespective of this, in our view a study of workers' wages over time should account for these earnings.

Unless otherwise noted, we drop a number of workers at the bottom of each year's earnings distribution, in order to select only those with reasonable labor market attachment. For years 1999 onward, we drop those with weekly earnings below $7\times$ the minimum wage, corresponding to one day's work for a low-wage worker. For the years before then, we scale the 1999 minimum wage by median real earnings growth to calculate a pseudo minimum wage. Our threshold is $7\times$ this value. When we use the annual earnings measure for robustness, we apply a 260*minimum wage rule, again using the pseudo minimum wage for years before 1999. For robustness, key results are presented without the removal of these lowest earners.

Throughout the paper, we refer to "raw," "residual," and "permanent" log earnings. *Raw log earnings* correspond to real weekly earnings above the threshold discussed in the previous paragraph, unless specified otherwise. *Residual log earnings* are the residual of raw log earnings regressed on individual age dummies for each year and each gender separately. *Permanent log earnings* in year t are the average of year $t-2$, $t-1$, and t earnings, including any earnings that fall below the threshold. Averaged earnings across these years are then residualized on age within year and gender. To be assigned a value for permanent earnings, individuals must have above-threshold earnings for at least 2 of the 3 years.

We draw on three samples, CS (cross-sectional), LX (longitudinal), and H (heterogeneity). The CS sample is made up of all those with earnings above the lower threshold. The LX sample is a subset of this group for whom we also observe above-threshold earnings for years $t+1$ and $t+5$, so that we can produce statistics based on 1- and 5-year changes. The H sample is a further subset, for whom we are able to build a measure of permanent income in $t-1$ as discussed above.[4]

Table 1 shows descriptive statistics for the CS sample by year. Panel (a) shows mean real weekly earnings for men and women, the share of female workers in the sample, and the age distribution. Panel (b) shows earnings percentiles.

Tables B1 and B2 in Appendix B in the Online Supplementary Material show summary statistics for the LX and H samples, respectively. Unsurprisingly, given the issue of missingness, conditioning on having 1- and 5- year earnings changes leads to a substantial drop in the sample size, as does having enough data to construct permanent income in the H sample. Comparing LX to CS, we lose around half of the sample. The LX sample is younger by construction, similar in income and slightly less female. Younger workers and those in the middle age bracket (36–45) are more likely to remain in the LX sample. Older individuals fall out of the sample when we require earnings at $t+1$ and $t+5$ due to the age restriction. Relative to the LX sample, the H sample is older. Younger workers are mechanically omitted due to a lack of earnings history. Given this, it is unsurprising that the H sample has higher earnings than both LX and CS.

2.2 *Firm-level data*

Our firm-level data comes from two sources. First, we use an ONS data set called the Annual Respondents Database (ARD),[5] which is constructed from the Annual Business Inquiry (ABI) survey. We use data from 2002 to 2014, the latest year available. The survey is a census of large establishments (250 employees or more) and a stratified sample of small and medium-sized enterprises.[6] Larger firms appear in the sample throughout, but smaller firms move in and out. Stratification for the smaller and medium-sized enterprises is based on industry, employment, and country. We use a measure of value added at factor cost at the firm level, which is derived by the ONS from reported turnover

[4]When presenting results from the LX and H samples using only 1-year forward differences, we do not require the sample to also have 5-year. This means that the LX and H sample differs depending on whether 1 or 5-year changes are being presented.

[5]Office for National Statistics. Virtual Microdata Laboratory (VML), University of the West of England, Bristol. (2017). Annual Respondents Database X, 1998–2015: Secure Access. [data collection]. 4th Edition. Office for National Statistics, [original data producer(s)]. UK Data Service. SN: 7989, http://doi.org/10.5255/UKDA-SN-7989-4.

[6]Sampling is actually performed at the reporting unit level, which in most cases coincides with the enterprise unit level.

Table 1. Descriptive statistics for CS sample by year.

(A) Earnings and demographics

Year	Obs	Fem inc	Male inc	% Fem	Age % 25–35	Age % 36–45	Age % 46–55
1975	93,082	309	599	36.0	36.0	30.0	34.0
1980	102,697	318	619	39.1	37.4	31.1	31.4
1985	99,449	362	681	41.3	37.0	33.7	29.3
1990	114,668	455	826	43.7	38.6	33.4	28.0
1995	115,072	494	841	46.4	38.6	31.5	29.9
2000	110,415	560	931	47.5	33.5	35.2	31.2
2005	114,028	648	1024	49.8	31.4	36.9	31.7
2010	119,105	670	1017	50.9	32.0	33.5	34.4
2015	121,036	634	914	51.6	34.1	30.4	35.4
2020	82,270	669	906	52.0	34.0	31.6	34.4

(B) Earnings percentiles

Year	Percentile 1	5	10	25	50	75	90	95	99	99.9
1975	85	145	193	326	470	623	792	925	1305	2186
1980	67	128	179	328	472	633	813	964	1403	2217
1985	66	125	187	343	506	690	921	1107	1649	2977
1990	75	147	220	394	594	836	1122	1382	2225	4411
1995	72	144	220	393	597	859	1164	1436	2313	4822
2000	84	168	246	429	650	942	1293	1624	2766	5628
2005	105	191	275	467	704	1038	1451	1840	3246	6235
2010	105	190	270	461	700	1046	1467	1877	3291	6781
2015	103	184	250	426	649	965	1350	1717	2852	5465
2020	119	202	273	456	661	971	1358	1717	2828	5289

Note: Summary statistics for the CS sample. All earnings figures are weekly earnings in 2018 USD. Panel (a) gives mean weekly earnings, the share female, and the share in each age bracket. Panel (b) gives earnings percentiles for both genders combined for each year. Source: ASHE.

and intermediate purchases. We then form our main labor productivity measure by dividing by employment. Our employment data is drawn from the Inter-Departmental Business Register (IDBR). While this approach represents the best-quality firm-level labor productivity data available, there is likely to be substantial measurement error. This will in part be due to misreported or misrecorded information on the components of productivity, but also due to timing issues, and particularly a timing mismatch between value added and employment.

To complement the ARD, we also use company accounts data from Bureau van Dijk's FAME database. This contains company accounts data, which we use to generate an alternative measure of value added, that we calculated as the sum of each firm's operating profit and total staff costs. We divide this by the number of employees in the FAME data, as reported in company accounts for that year. Again, for the reasons discussed above there will likely be a high degree of measurement error in this calculation.

Both measures of firm value-added per worker can be matched to the wage data using company identifiers. Further details of the firm-level data and the match with the wage data are provided in Appendix B in the Online Supplementary Material.

3. Descriptive patterns in inequality, volatility, and mobility

Here, we provide a battery of descriptive patterns covering income inequality, volatility, and mobility. We provide historical context where appropriate and refer the reader to Appendix A for more details on macroeconomic trends and labor market institutions.

3.1 *Inequality*

Much has been written on the long-term trend of rising UK wage inequality. A succinct review of inequality patterns and research contributions is provided by Hills et al. (2010), Machin (2011), and more recently in Brewer (2019). The ongoing Deaton review at the Institute for Fiscal Studies will present a thorough overview of wage inequality and how it relates to household income inequality. The patterns we show here are consistent with this existing evidence and provide important background to the following sections on volatility and mobility.

Figure 1 shows trends in log earnings percentiles. In panel (a), we can see strong male median real wage growth throughout the 1980s, late 1990s, and early 2000s. The period since the 2008 recession has been characterized by an extended decline in real wages, with only partial recovery in the final part of the sample. As will be more clearly demonstrated in the figures to follow, the period saw a widening of the wage distribution, with the greatest wage growth being felt at the top percentiles. Panel (b) shows a contrasting picture for female workers. Median wage growth has been stronger and shows more signs of recovery post-2008. While the top percentiles have growth fastest over the period as a whole for women, wage growth has occurred across the distribution.

Panels (c) and (d) demonstrate a pronounced fanning out of earnings within the top decile of the earnings distribution, with the top 0.01% of earners seeing the largest growth over the period. Figure C1 in Appendix C in the Online Supplementary Material shows the statistics for both genders combined.

As discussed in Section 2 and Appendix B, the weekly measure in this data set is not ideal for studying top earners. In Figure C2 in Appendix C, panels (a) and (b), we compare trends in annual and weekly earnings at the top for the years where annual earnings are also available.[7] We see that the weekly measure understates the growth of top earnings in the 2000s relative to the annual measure. Top percentile earnings growth for men between 1998 and 2008 using the annual measure is between $1.5\times$ and $2\times$ as large as that suggested by the weekly measure, consistent with the results of Bell and Van Reenen (2014). Lower percentiles are more consistent across the weekly and annual measures. This is unsurprising, as for most workers bonuses do not account for a large share of earnings. In panel (c) of Appendix Figure C2, we can see that the 90–10 ratio is

[7]These figures compare only those workers in their job for over a year, so that we can construct a valid annual measure.

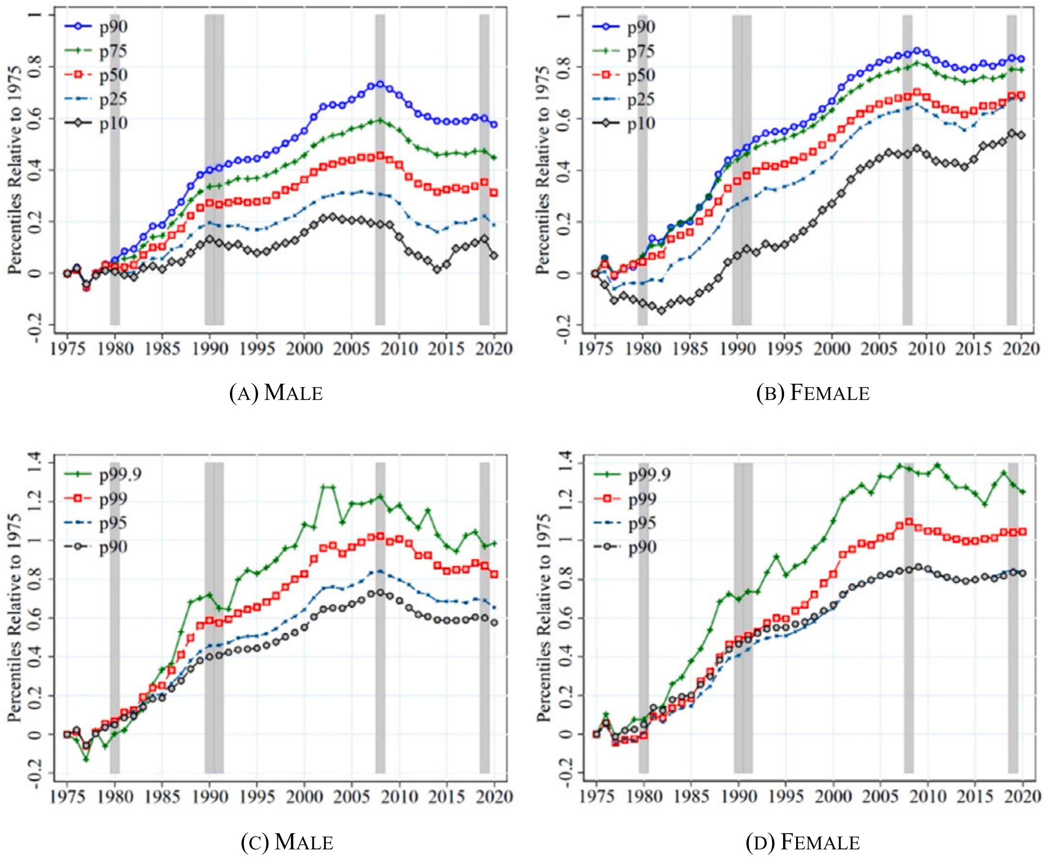


FIGURE 1. Change of percentiles of the log real earnings distribution. Notes: Raw log earnings and the CS sample. All percentiles normalized to 0 in 1975. Shaded areas are recessions. Source: ASHE.

almost identical for the weekly and annual earnings measures. For most of the distribution, weekly earnings match annual earnings well. The difference is greatest for the most recent year (2020), which is unsurprising given the timing of the Covid-19 shock, just before the weekly measure is recorded in April.

Figures C3 and C4 in Appendix C show the pareto tails at the top 1% and top 5% for each gender. This shows that for both genders, between 1975 and 2015 the top tails of the earnings distribution have become fatter. For men, this primarily happened in the first half of the sample. Between 1995 and 2015, the slope in the top 5% become slightly steeper, suggesting a drop in dispersion. For women overall, we also see a fattening of the tails. In the 1% measure, from 1995 to 2015 there is a slight narrowing, but this is not present in the 5% measure. Due to the concerns over top earnings when using the weekly earnings measure, in Figures C5 and C6 we show the tails for 2000 and 2015 using annual earnings. The tails are substantially fatter when these measures are used. For both genders, there is a marginal narrowing of the tails from 2000 to 2015. This again

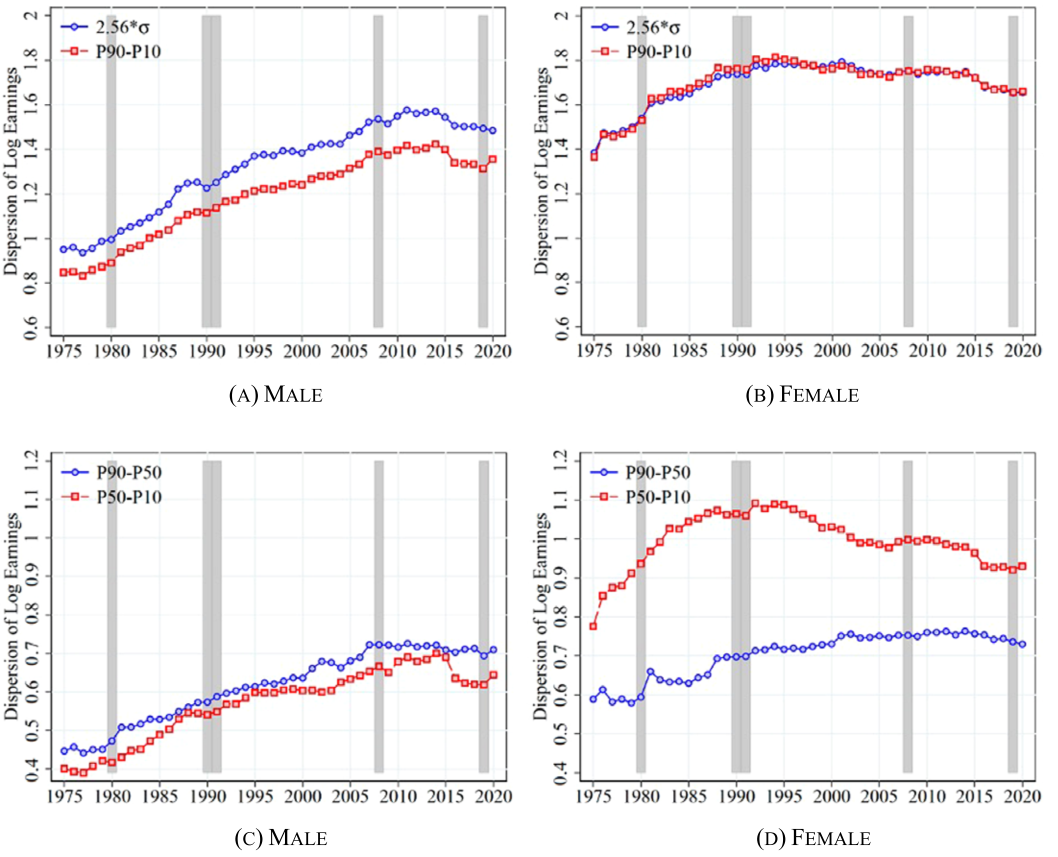


FIGURE 2. Log earnings dispersion. Notes: Raw log earnings and the CS sample. Shaded areas are recessions. $2.56 * \sigma$ corresponds to the P90-10 differential for a Gaussian distribution. Source: ASHE.

highlights the importance of focusing on annual earnings when examining the very top of the distribution.

Figure 2 shows trends in earnings dispersion. In panel (a), we can see the steady increase in male earnings inequality both for the parametric ($2.56 *$ standard deviation) and non-parametric (P90–P10) measure. This increase has tapered off and gone into decline since 2010, though dispersion remains high relative to previous decades. In panel (b), we see that for women, inequality has been roughly flat or falling since the mid-1990s. Panels (c) and (d) decompose aggregate dispersion into right tail (P90–P50) and left tail (P50–P10) dispersion. For men, we can see that both right- and left-tail dispersion have contributed to the overall rise in inequality over the period. The decline in inequality felt in recent years comes entirely from the P50–P10 tail. Returning to Figure 1, we see that significant wage growth in the 10th percentile has resulted in a closing of the gap between the lowest and average earners. For women, the picture is different. We see that the substantial rise in inequality from 1975–1995 was driven primarily by increases in P50–P10. Since the mid-1990s, this has been in decline. P90–P50 on the other hand has been increasing steadily throughout, up until the most recent years. Figure C1 in Appendix C shows the statistics for both genders combined.

It has been argued that since its introduction in 1999 the minimum wage has successfully propped up the lower part of the earnings distribution, particularly among women.[8] This is consistent with that, though the fall in female P50–P10 predates its introduction. The largest single-year increase in the minimum wage relative to average real wages came in 2016, with the introduction of the National Living Wage (NLW), which was effectively a large increase in the minimum wage. In both the female and male wage distributions, it is possible to see the strong 1-year increase in the 10th percentile, and a substantial drop in P50–P10 for this year. The rising minimum wage coupled with low aggregate real wage growth has led to a decline in the dispersion of earnings.

Considering the period as a whole, there have been many explanations offered for the rise of wage inequality. Increasing education premiums account for some of the gap, with the wage gaps between graduates and nongraduates rising particularly fast throughout the 1980s and 1990s. A key factor underpinning rising inequality has been a relative increase in the demand for skilled workers. Labor market polarization (Goos and Manning (2007)) is also part of the story, with the share of jobs with the lowest and highest average occupational pay growing the fastest. Various studies of skill-biased technical change (Berman, Bound, and Machin (1998) and Machin and Van Reenen (1998)) have found support for technology being an important part of the story of rising wage inequality in the UK.

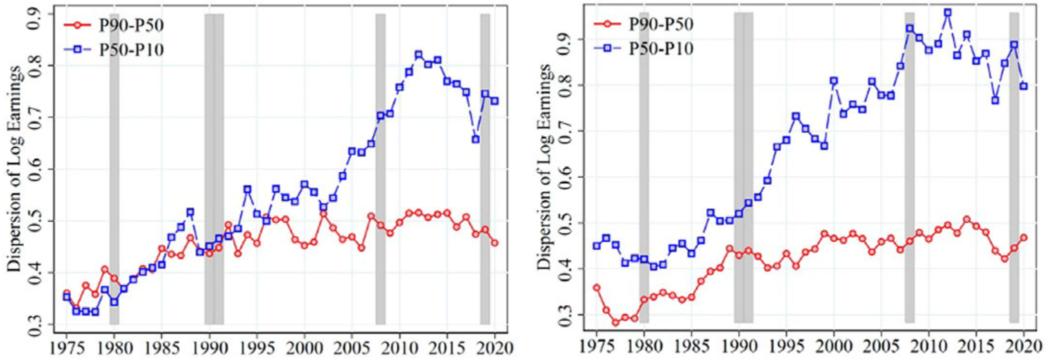
An advantage of the ASHE data is that we can decompose increases in earnings inequality into hourly wage and hours components as follows:

$$\text{var}\big(\log(y)\big) = \text{var}\big(\log(w)\big) + \text{var}\big(\log(h)\big) + 2\,\text{cov}\big(\log(w), \log(h)\big),$$

where y is (weekly) earnings, w is the hourly wage, and h are hours worked. Figure C7 in Appendix C shows this decomposition for men and women separately. Turning to the figure for men, we see that for the first 25 years of the sample, inequality in weekly earnings tracks inequality in hourly wages closely. From the early 2000s, however, the two diverged. For men, the variance of hours and the covariance term has become an increasingly significant component of weekly earnings inequality. This is driven by a growing share of men working few hours for low hourly wages. This is a striking pattern, and one which merits additional future study.

The covariance between hours worked and hourly wages of men became positive in 2014 and 2015, for the first time in 40 years. For women, the variance of hours has always played a larger role in aggregate earnings inequality. Panel (b) of Figure C7 shows that for women the contribution of each factor has remained roughly constant, all three contributing to the rise in inequality until the mid-1990s, and all three being broadly stable since, with the exception of the previous 5 years. Hours inequality has increased in the most recent years, coupled with a decline in the covariance between hours and hourly wages.

[8] The Low Pay Commission (LPC (2020)) states that in 1999, 3.4% of jobs were covered. By 2018, this had grown to 7.0%.



(A) MALE (B) FEMALE

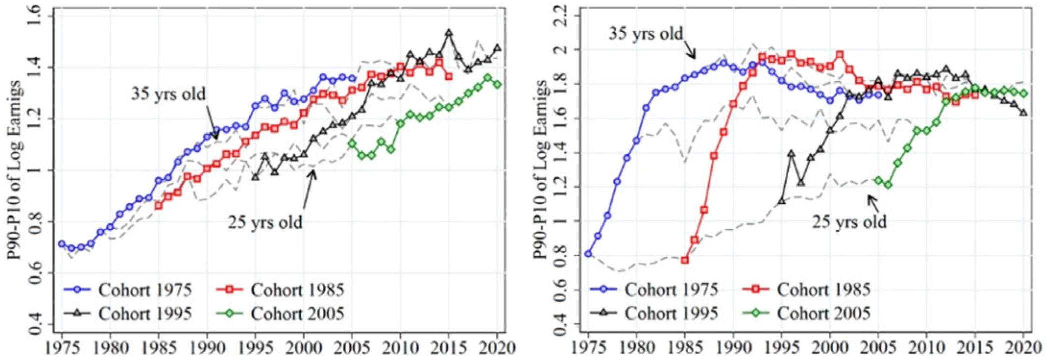
FIGURE 3. Income inequality for those aged 25. Notes: Raw log earnings and the CS sample aged 25. Shaded areas are recessions. Source: ASHE.

In terms of income shares, Figure C8 in Appendix C shows a significant growth of the top quintile, at the expense of all other quintiles. The figure also shows a precipitous drop in the income share of the bottom 50% from 1975 to 2008, and a partial recovery in the years since. As this is using the weekly earnings measure, this figure underestimates the share going to the very top as discussed previously. Figure C9 shows the same pattern in the Gini coefficient. Inequality rises precipitously until the Great Recession and has been in decline since then. In both the Gini coefficient and in the share of earnings going to the bottom quintile, we can see the impact of the minimum wage hike in 2016.

Figure 3 shows inequality for those aged 25, close to the start of a workers' career.[9] In panel (a), we see that male bottom-tail inequality has been rising throughout most of the period, particularly since the early 2000s. The top-tail inequality has been relatively stable. The picture is broadly similar for female workers aged 25, though the sharp increase in bottom-tail inequality began earlier. There is a marked difference between the aggregate inequality patterns shown previously and those seen among the youngest workers.

In Figure 4, we show how earnings inequality progresses over the life cycle for different cohorts. For example, the 1975 cohort here refers to workers aged 25 in 1975, so those born in 1950. The 1975 cohort line shows earnings inequality among these workers throughout their working lives. The dashed lines show earnings for individuals of 25, 30, 35, and 40 years of age over time, as indicated by the arrow markers. For men, we see that inequality is increasing at a steady and relatively constant rate within a cohort as each cohort ages. Comparing the two figures, we see that dispersion changes over the life cycle more for women (panel (b)) than for men (panel (a)). Women see a large increase in dispersion between ages 25 and 35. For women, all of the increase in dispersion comes in the first decade of labor market experience, unlike among men for whom dispersion increases over the life cycle. This difference is almost entirely driven by selection into part-time work for women. In the 1975 cohort, for example, the share of part-time work-

[9]In the UK, it is unusual to remain in tertiary education past the age of 25.



(A) MALE (B) FEMALE

FIGURE 4. Life-cycle inequality over cohorts. Notes: Raw log earnings and the CS sample. Dashed lines correspond to earnings of 25-, 30-, 35-, and 40-year-olds as indicated by arrows. Each solid line corresponds to an individual cohort, where "cohort X" represents the cohort aged 25 in year X. Source: ASHE.

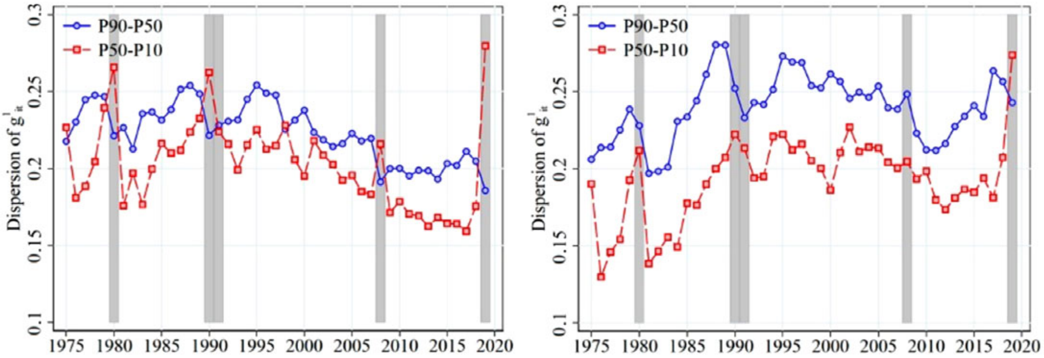
ers rises from 13% to 45% for women between the ages of 25 and 35, while it remains very low for men (1% and 3%, respectively).[10]

3.2 *Volatility, skewness, and kurtosis*

Similar to what has been found in the US, studies of income and earnings volatility in the UK have found a variety of results, which are not always consistent with one another and vary by data set and methodology. Most of the existing work on income dynamics in the UK has used survey data and is best reviewed in Jenkins (2011a). The BHPS has been used in Jenkins (2011b) and Cappellari and Jenkins (2014), the latter of which uses nonparametric measures like those of this paper, finding a slight decline in earnings volatility. Devicienti (2011) fits several variance component model specifications to BHPS data and finds little change over time. Ramos (2003) on the other hand uses the same data to show an increase in the transitory component of earnings from 1991–1999. Dickens (2000) finds an increase in the transitory variance of earnings using the New Earnings Survey from 1985–1995. Dickens and McKnight (2008) using the Lifetime Labor Markets Database (LLMDB) find falling mobility for men. Kalwij and Alessie (2007) use NES data to show increases in both the transitory and permanent component of wages between 1975 and 2001.

We contribute to this literature by examining a longer time period and using nonparametric methods, which are increasingly recognized for their robustness and rely on few assumptions of underlying earnings processes, but which require a large amount of data. We present various statistics on workers' earnings changes over 1-year and 5-year periods. To paint a full picture of the distribution of earnings changes, Figures C10 to

[10]The P90–P10 log differential for women rises from 0.81 to 1.84 for the 1975 cohort from ages 25 to 35 (Figure 4). For women in full-time employment, the rise is from 0.70 to 0.96—almost identical to the rise for men (0.71 to 0.96).



(A) MALE (B) FEMALE

FIGURE 5. Dispersion of 1-year log earnings changes. Notes: Residual 1-year earnings changes (g_{it}^1) and the LX sample. Shared areas are recessions. Source: ASHE.

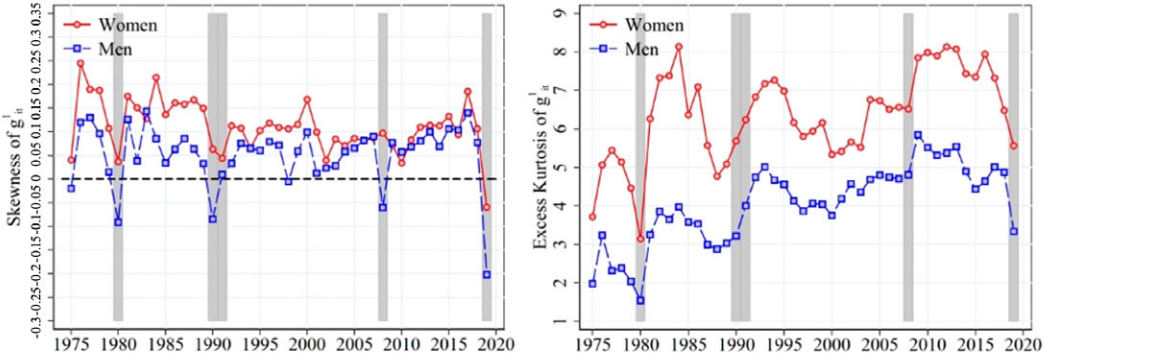
C13 in the Appendix show the densities and log densities of earnings changes for 2005.[11] These figures show that consistent with the US evidence in Guvenen et al. (2021) earnings changes are leptokurtic, exhibiting substantial deviations from the log normal distribution. In terms of skewness, for 1-year earnings changes we find a relatively symmetric distribution. For 5-year changes, we find negative skewness, in line with the recent US evidence.[12] In Figure 5, we show top- and bottom-tail dispersion in 1-year log earnings changes. In panel (a), we see spikes in P50–P10 and drops in P90–P50 around recessions for men. The spike in the most recent recession (2020) stands out as an outlier. The most recent recession dwarfs the previous three in terms of its effect on lower-tail wage volatility. For both men and women, the P50–P10 statistic is higher in 2020 than in any previous period. As will be discussed later in this article, this likely stems from large wage cuts associated with being furloughed during the Covid-19 shock.

In terms of aggregate volatility, as measured by the sum of P90–P50 and P50–P10, for men there appears to have been a decline in volatility from the mid-1990s onward, with fewer workers seeing large wage changes relative to the median. As in the US, this was a period of macroeconomic stability in the UK, and the patterns here match those in Sabelhaus and Song (2010). The trend is less clear for women and is not as visible in 5-year changes presented in Figure C14 in the Appendix.

Figure 6 shows nonparametric measures of skewness and kurtosis of 1-year earnings changes over time. Reflecting the patterns discussed in the previous figure, Kelley skewness is strongly pro-cyclical, dropping in recessions. The pattern is more visible for men than for women, reflecting a greater sensitivity to business cycle fluctuations among male workers. This figure also again shows the scale of the 2020 shock, with male and female earnings changes reaching their lowest skewness of any year across the 45-year period. There does not seem to be any aggregate trend in Kelley skewness, and for most periods, earnings changes exhibit a mild positive skew.

[11] 2005 was chosen as an example recent year in a stable growth period.

[12] The lack of any skewness in 1-year changes may reflect the undersampling of movers in the ASHE data set (see Appendix B). Where possible, we present both 1- and 5-year earnings changes.



(A) SKEWNESS (B) KURTOSIS

FIGURE 6. Skewness and kurtosis of 1-year log earnings changes. Notes: Residual 1-year earnings changes (g^1_{it}) and the LX sample. Shared areas are recessions. Kelley skewness is $\frac{(P90-P50)-(P50-P10)}{(P90-P10)}$. Excess Crow–Siddiqui kurtosis calculated as $\frac{P97.5-P2.5}{P75-P25}-2.91$, where the first term is Crow–Siddiqui kurtosis and the second is the value of this measure for the normal distribution. Source: ASHE.

In panel (b) of Figure 6, we see that excess Crow–Siddiqui kurtosis of earnings changes is trending upward for workers of both genders. This appears to be a previously unreported result. Figure C15 in the Appendix shows the spread of earnings changes for a variety of percentiles. We see that for both genders, the gap between central percentiles, for example, P62.5 and P37.5 has fallen while the gaps between the top and bottom tails have remained relatively constant. Earnings changes have become more clustered around the median over time, leading the distribution of changes in earnings to become more leptokurtic. The same is true for 5-year changes, as shown in Figure C16 in the Appendix. Kurtosis exhibits some cyclicality, rising after recessions.

The finding of rising kurtosis is novel, and so we perform several tests to check its robustness and to explore potential explanations. First, in Figure C17 in the Appendix we divide the sample into job movers and job stayers. This shows that the patterns are present in both groups for men, and primarily there for stayers among women. Rising kurtosis is not driven by changes in the ability of ASHE to trace job movers, which we discuss as a potential concern in the data section above. In Figures C18–C20, we show that rising kurtosis is seen across broad industrial sectors, among union and nonunion covered wages, and in both the public and private sector. In Figure C21, we show that these patterns are not driven by the specified lower earnings threshold, below which individuals are dropped. If we do not make this cut and instead include all individuals, including the lowest earners, we see almost identical results.

Why has kurtosis risen? Part of the story may again come from the relative stability in the economy from the mid-1990s onward. It is plausible that steady growth and low inflation allow firms to better smooth pay progression over years, leading to a compression around median wage changes. This would suggest that the UK has experienced its own "great micro moderation," in which more workers are seeing earnings changes close to the median.

In Figure 7, we plot several statistics of changes in residual earnings across 20 quantiles of the permanent income distribution.[13] The top quantile has been divided in half such that the highest statistic refers to those above the 97.5th percentile. Due to our relatively low sample and the issues of earnings measurement at the top end of the earnings distribution, we are unable to comment in detail on the distribution of earnings changes of those at the very top, unlike in countries with access to full population data. Across most of the distribution, the patterns we find here are close to that of other countries, particularly those shown for the US in Guvenen et al. (2021).

For consistency, in the main text here we look at 1-year changes using nonparametric measures. The equivalent 5-year figures and versions for both intervals using parametric alternatives are presented in Appendix Figures C22–C24 and tend to show clearer patterns than those in the main text.

In terms of 1-year earnings change dispersion, among men we observe strong differences by age. For younger men, the pattern is U-shaped, with the lowest and the highest earners experiencing a high spread of earnings changes. For older men, we see a more monotonic pattern, with the spread declining in permanent earnings across most of the distribution before an uptick toward the top of the distribution. In the Appendix, Figure C22 shows similar patterns for 5-year earnings changes. Figures C23 and C24 show a U-shape for all ages for the parametric measures.

Panel (b) of Figure 7 shows that female earnings spreads are high lower down the distribution, which likely reflects high dispersion among part-time workers. Among young women, there is something of a U-shape. Appendix Figures C22–C24 show these results to be robust across 5-year changes and using parametric measures.

Panels (c) and (d) of Figure 7 show how Kelley skewness varies across the permanent income distribution. For men, again we see differences by age. Younger workers' earnings changes are more positively skewed, and this is declining in permanent income. For female workers, Kelley skewness is the lowest for younger workers. For both genders, Kelley skewness is declining in permanent earnings. Again, Appendix Figures C22–C24 show similar patterns. Five-year changes are more negatively skewed than 1-year changes.

Panels (e) and (f) of Figure 7 show the excess Crow–Siddiqui kurtosis patterns. We see that across most of the distribution, kurtosis is increasing in permanent income. It is highest for older workers, who also exhibit the greatest upward-sloping pattern in permanent income. For men, there is an uptick in kurtosis toward the bottom of the distribution. Once more, Appendix Figures C22–C24 show similar patterns.

3.3 *Mobility*

In this section, we present patterns of wage mobility. Whereas the previous section on volatility focused on absolute wage changes, here we look at how individual workers' positions in the income distribution evolves over time.

[13]As ASHE is only a 1% sample of workers, the estimates presented here are relatively noisy. We have applied a smoother to remove some of this noise. The permanent income distribution is evaluated over the most recent 20 years of data, 2001–2020.

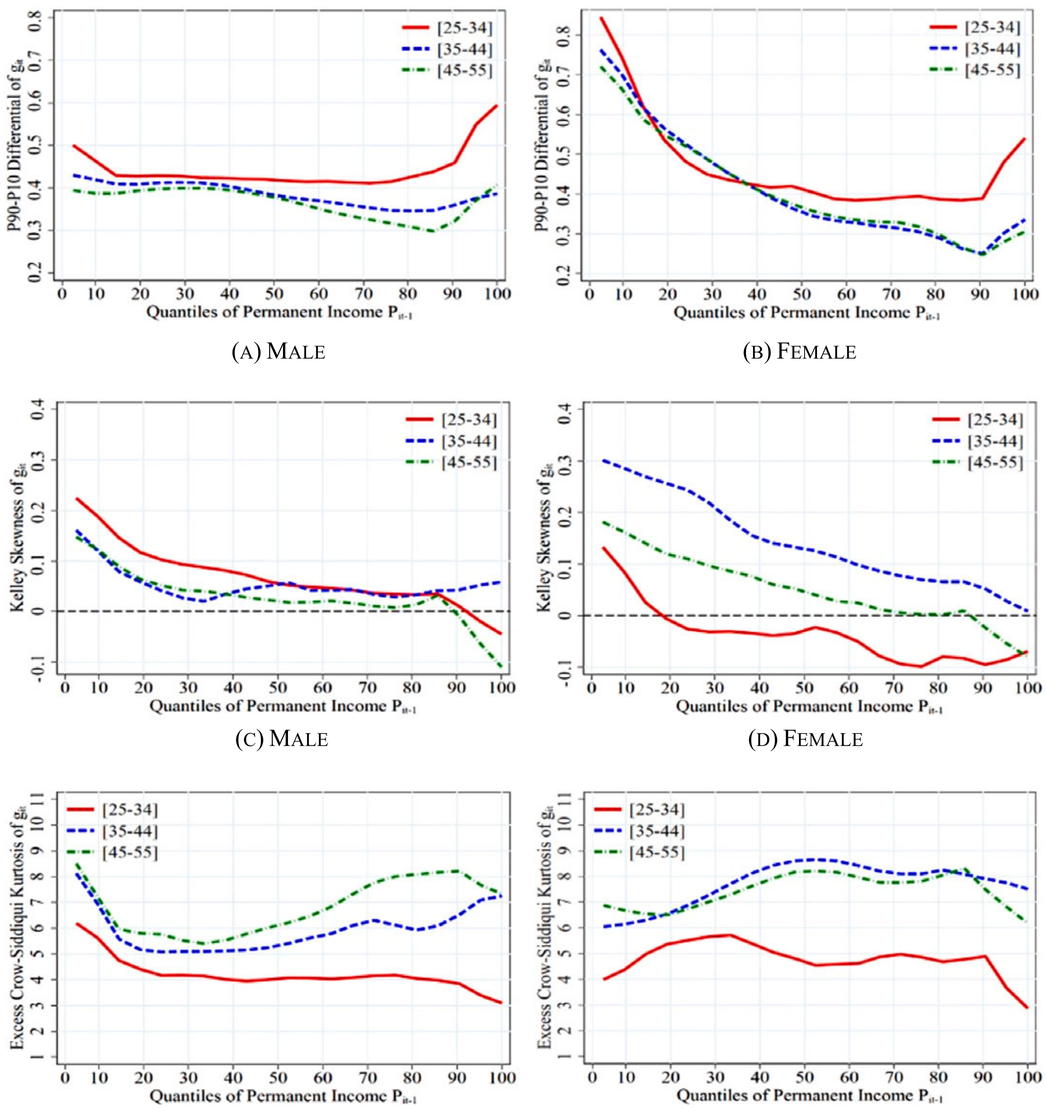
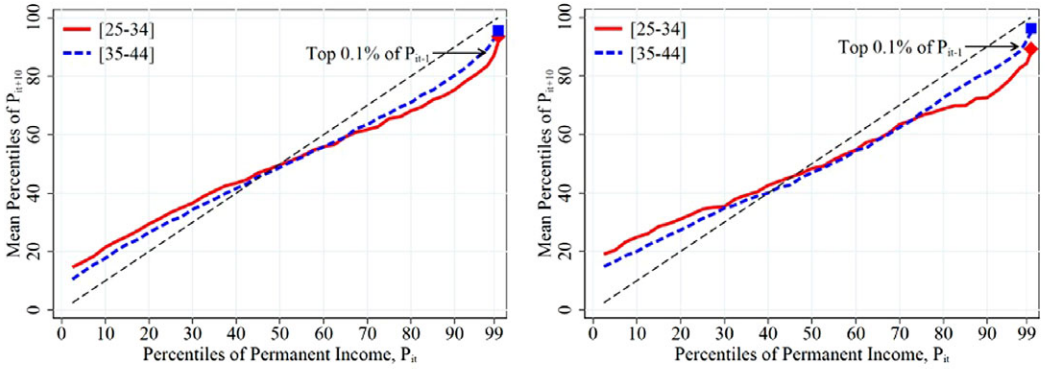


FIGURE 7. Dispersion, skewness, and kurtosis of 1-year log earnings changes. Notes: Residual 1-year earnings changes and the H sample. Kelley skewness is $\frac{(P90-P50)-(P50-P10)}{(P90-P10)}$. Excess Crow–Siddiqui kurtosis calculated as $\frac{P97.5-P2.5}{P75-P25}-2.91$, where the first term is Crow–Siddiqui kurtosis and the second is the value of this measure for the normal distribution. Permanent income calculated using earnings from $t-1$, $t-2$, and $t-3$ as described in the text. Calculations are based on data from 2001–2020. Source: ASHE.

Figure 8 shows 10-year mobility for two different age groups. The lines give the mean percentile of workers in the $t+10$ permanent income distribution for workers at different points in the permanent income distribution at year t. Permanent income is defined as in the data section above. The dashed diagonal black line corresponds to perfect im-



(A) MALE (B) FEMALE

FIGURE 8. Evolution of 10-year mobility over the life cycle. Notes: Permanent income and sample containing all those with permanent income at t and $t + 10$. Permanent income calculated using earnings from t, $t - 1$, and $t - 2$ as described in the text. Workers placed into 41 bins on the x-axis, where the top bin refers to top 0.1% of earners and all other bins correspond to evenly spaced quantiles. Calculations are based on data from 2001–2020. Source: ASHE.

mobility. For both men and women, we see that stickiness is greater at the top of the distribution than the bottom, with the curve lines becoming steep in the top few percentiles. Mobility is declining in age for both genders. As workers age, their position in the income distribution becomes stickier. Figure C25 in the Appendix shows similar patterns for 5-year mobility. This also shows that mobility for 45–55-year-olds is close to that of 35–44-year-olds. The age profile in mobility weakens at greater ages.

Figure 9 shows how 10-year mobility has evolved over time. For men, we see a decline in mobility from 1977 through 1990 to 2015. To the left of the intersection with the 45-degree line, the line for the first year is above those for the later years. To the right of the intersection, it lies below them. Stickiness at the top increased from 1977 to 1990, before falling back somewhat in 2005. This is consistent with Dickens and McKnight (2008), who find that male earnings mobility fell throughout the 1980s and 1990s. For women, there is little change across most of the distribution, though 10-year stickiness has increased toward the top of the distribution. Figure C26 in the Appendix show broadly similar patterns for 5-year mobility. Figure C27 in the Appendix compares 10-year mobility using the annual earnings measure to 10-year mobility using the weekly earnings measure, for those for whom we can construct a robust measure of annual earnings. We see that for women the two coincide. For men, mobility based on annual earnings is lower than that based on weekly earnings. This likely reflects a greater role of bonus pay for the mobility of men.

4. WAGES AND HOURS RESPONSES TO AGGREGATE AND FIRM-LEVEL SHOCKS

In this section, we exploit the long-time dimension of our data set and the availability of information on hours, to explore how aggregate and firm-level shocks affect workers' wages and hours. We also exploit the recent availability of data for 2020 to examine the impact of the Covid recession and compare it with previous recessions.

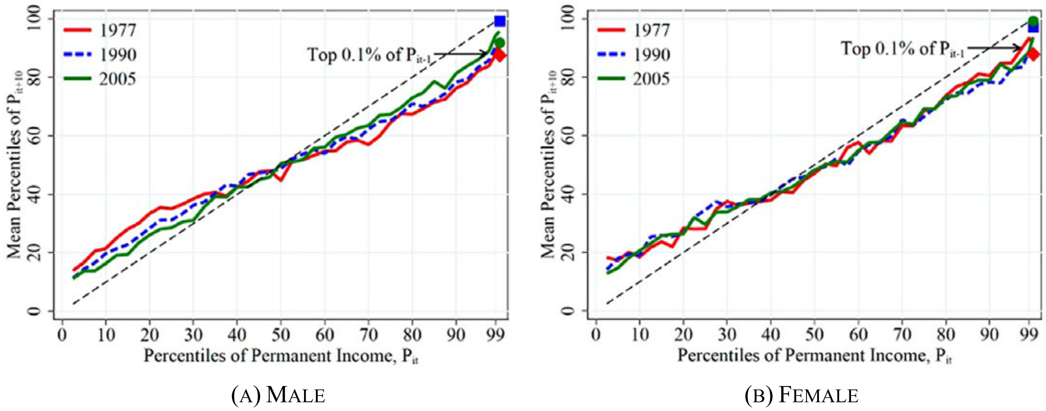


FIGURE 9. Evolution of 10-year mobility over time. Notes: Permanent income and sample containing all those with permanent income at t and $t + 10$. Permanent income calculated using earnings from t, $t - 1$, and $t - 2$ as described in the text. Workers placed into 41 bins on the x-axis, where top bin refers to top 0.1% of earners and all other bins correspond to evenly spaced quantiles. Source: ASHE.

4.1 *Aggregate shocks*

We begin by examining how workers' wages and hours respond to changes in real GDP. This relates to a recent literature using administrative data (Guvenen et al. (2017)) and an older literature on wage cyclicality (Devereux and Hart (2006)). In column (1) of Table 2, we report the estimated elasticity of (weekly) earnings with respect to GDP, obtained by regressing changes in log weekly earnings on changes in annual log real GDP. The estimate, which we will refer to as "GDP beta," is 0.381, meaning that a contemporaneous 1% increase in real GDP is associated with an increase of roughly 0.4% in real weekly earnings.[14] In column (2), we allow for lagged effects of GDP on wages. Two key results emerge. First, the total effect of a GDP shock on wages is now 0.780 (and if a third lag was included this would rise to 1.159) comparable with estimates for the US, and second, the contemporaneous effect remains almost the same as in column (1). In column (3), we include an indicator for whether the economy is in recession, defined by a period of negative real GDP growth, while in column (4) we allow for asymmetries in the elasticity, interacting the recession indicator with GDP growth. Columns (3) and (4) make it clear that there are strong asymmetries. Column (4) shows that in nonrecession years, the elasticity is 0.73, almost double the aggregate number from column (1). Out of the 45 years for which we construct earnings changes, only 5 are recessions. These 5 years have a strong impact on the overall GDP beta. This suggests that estimates of GDP beta require long-time dimensions to be estimated robustly. With short panels, the estimated coefficient will strongly depend on the number of recession years in the sample. We believe that this makes international comparisons of GDP beta estimates

[14]We have performed an exercise in which we compare the GDP response of annual earnings to that of weekly earnings. For the overlapping years, the estimates approximately coincide.

TABLE 2. GDP beta estimates.

	Earnings				Hours			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔGDP	0.381	0.297	0.552	0.730	0.155	0.163	0.046	0.050
	(0.01)	(0.006)	(0.01)	(0.01)	(0.00)	(0.005)	(0.01)	(0.01)
ΔGDP(−1)		0.238				−0.028		
		(0.006)				(0.005)		
ΔGDP(−2)		0.245				0.017		
		(0.005)				(0.004)		
Recession			0.015	0.007			−0.009	−0.010
			(0.00)	(0.00)			(0.00)	(0.00)
ΔGDP ∗ Recession				−0.680				−0.017
				(0.02)				(0.02)
Constant	0.029	0.021	0.024	0.019	0.001	0.001	0.004	0.004
	(0.00)	(0.000)	(0.00)	(0.00)	(0.00)	(0.000)	(0.00)	(0.00)
R-Sq	0.001	0.002	0.001	0.001	0.000	0.000	0.000	0.000
N	4,575,704	4,575,704	4,575,704	4,575,704	4,575,704	4,575,704	4,575,704	4,575,704

Note: Dependent variable in columns (1)–(4) is a change in real log weekly earnings and in columns (5)–(8) is a change in log hours worked. Standard errors clustered by worker. Years 1975–2020. Source: ASHE

challenging, as they will likely depend on the available data sample. The negative coefficient on the recession interaction in column (4) demonstrates that workers are protected from large earnings declines during recessions, consistent with previous UK evidence in Gregg, Machin, and Fernández-Salgado (2014).

In columns (5)–(8), we repeat the exercise for changes in log hours of work. From column (5), we can see that the hours responses are relatively large. The coefficient of 0.155 is around two-fifths of the coefficient in column (1), suggesting that a significant share of the response of weekly earnings to aggregate fluctuations can be explained by changes in hours worked. Given the discussion of our hours variable in the data section, if anything, this is likely to be an underestimate of the importance of hours. Column (6) shows that in contrast to earnings, there is little inertia in the responsiveness of hours to GDP shocks. Columns (7) and (8) again show strong asymmetries. In nonrecession years, the coefficient falls below 0.05. Comparing the first row of column (8) to that of column (4) suggests that in nonrecession years, only a small share of the weekly earnings response can be explained by hours changes.[15]

The results of Table 2 are consistent with the large body of work on wage rigidities. In recessions, as hourly wages cannot be reduced sufficiently, to reduce labor costs firms reduce hours of work. In times of economic growth, hours are relatively unresponsive to differences in growth rates. Instead, adjustment comes through hourly wages. It should be noted that we cannot capture extensive margin adjustments to aggregate shocks with this data. We only observe wages and hours for those workers employed in the reference

[15]Almost identical coefficients are obtained if we use real gross value-added per worker rather than real GDP as out measure of the business cycle. GVA-per-worker is used in the section on firm betas.

week, so any unemployed workers are omitted. While annual earnings are available in the data from 1998 (and were examined in Section 3), these data also only relate to the annual earnings in the current job rather than covering all employment earnings over the previous 12 months. As a result, we are likely to underestimate the worker betas as evidence from other countries suggest they are larger when the extensive margin response is included (Hoffmann and Malacrino (2019) and Guvenen et al. (2017)).

Next, we explore how the estimated GDP beta varies across worker characteristics, asking whether workers bear the incidence of aggregate shocks equally. We find patterns that closely match those for the US presented in Guvenen et al. (2017). In Table 3, column (1), we interact the change in GDP with gender. We see that womens' earnings are less responsive to aggregate shocks, with an estimated elasticity of 0.28 relative to an estimate of 0.47 for men. In column (2), we interact with a set of age group dummies. Responsiveness is highest for the youngest workers (the omitted group), decreasing with age for most of the distribution before rising again for the oldest workers. In column (3), we include an indicator for the public sector and an indicator for unionization. As the two are highly correlated, unlike in the other columns we include both predictors in the same regression. We see that both have a dampening effect on the estimated relationship. Those in the public sector experience half the aggregate earnings risk of those in the private sector.

Next, in column (4) we include firm size dummies. Responsiveness to aggregate shocks is highest for workers with the smallest employers (the omitted group). Those working for employers with 2000 or more employees have an estimated GDP beta, which is a quarter of that of those at employers with under 100 employees. In column (5), we estimate heterogeneity by skill level. The earnings of those in higher skilled occupations are less responsive to GDP. Those in a high skilled occupation bear around one-third of the aggregate earnings risk as those in low skilled occupations.[16] Finally, in column (6) we report heterogeneity estimates by quantile of the wage distribution (an alternative skill measure), which again points to reduced exposure to aggregate fluctuations for the most skilled.

In Appendix D of the Online Supplementary Material, we report the results of two additional robustness tests. First, in Table D1 we replicate the results of Table 3 allowing for two lags of GDP. The patterns are consistent with those discussed above, though they tend to be more substantial. Second, to address concerns over data coverage in the ASHE data, particularly of job movers, we estimate GDP betas using the UK Household Longitudinal Study (UKHLS). This data set is discussed in Appendix B and has data on gross monthly wages from 1991–2018. It should be noted that the sample size is an order of magnitude smaller than ASHE and covers only the second-half of the main sample. The first column of Table D2 shows that the aggregate contemporaneous GDP elasticity is 0.528 using this data—broadly similar to the 0.381 in the first column on Table 2. If we allowed for two additional lags of GDP, the overall elasticity would rise to 1.221—again highlighting the importance of wage inertia. The subsequent columns of the table

[16] For this column, we are only able to use data from 2011 onward, so these estimates will to a significant extent be driven by the most recent Covid-19 recession.

Table 3. Log earnings GDP beta heterogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔGDP	0.470	0.450	0.541	0.720	1.008	0.398
	(0.01)	(0.02)	(0.01)	(0.02)	(0.04)	(0.02)
ΔGDP × Female	−0.189					
	(0.01)					
ΔGDP × 25–34		−0.084				
		(0.03)				
ΔGDP × 35–44		−0.077				
		(0.03)				
ΔGDP × 45–54		−0.167				
		(0.03)				
ΔGDP × 55–64		−0.060				
		(0.03)				
ΔGDP × Public			−0.278			
			(0.01)			
ΔGDP × Union			−0.184			
			(0.01)			
ΔGDP × 100–499				−0.175		
				(0.03)		
ΔGDP × 500–1999				−0.370		
				(0.03)		
ΔGDP × 2000+				−0.566		
				(0.02)		
ΔGDP × Mid-Skill					−0.423	
					(0.05)	
ΔGDP × High-Skill					−0.642	
					(0.05)	
ΔGDP × Q2 Earnings						0.070
						(0.02)
ΔGDP × Q3 Earnings						0.055
						(0.02)
ΔGDP × Q4 Earnings						0.007
						(0.02)
ΔGDP × Q5 Earnings						−0.072
						(0.02)
R-Squared	0.001	0.020	0.002	0.001	0.004	0.003
N	4,575,704	4,575,704	4,575,704	2,555,948	995,963	3,269,512

Note: Dependent variable is change in real log weekly earnings. Sample held fixed for columns (1)–(3). The sample is lower in columns (4)–(6) due to missing variables. Standard errors clustered by worker. Years 1975–2020. Source: ASHE.

examine the heterogeneity in the estimated betas. The pattens that we observe in the ASHE data are broadly replicated with this alternative data set—women, union members, workers in larger firms, and those further up the pay distribution have smaller estimated elasticities. One difference is that there is no obvious pattern across the age distribution using UKHLS data—though again if we allow for additional lags of GDP we get the same age pattern as with the ASHE data.

In Table 4, we perform the same exercise with hours as the outcome variable. In column (1), we can see that as was the case with earnings, womens' hours are less respon-

TABLE 4. Log hours GDP beta heterogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔGDP	0.189 (0.01)	0.056 (0.02)	0.154 (0.01)	0.161 (0.02)	0.618 (0.04)	0.153 (0.01)
ΔGDP × Female	−0.068 (0.01)					
ΔGDP × 25–34		0.073 (0.02)				
ΔGDP × 35–44		0.112 (0.02)				
ΔGDP × 45–54		0.083 (0.02)				
ΔGDP × 55–64		0.164 (0.02)				
ΔGDP × Public			−0.057 (0.01)			
ΔGDP × Union			0.055 (0.01)			
ΔGDP × 100–499				0.008 (0.02)		
ΔGDP × 500–1999				−0.054 (0.02)		
ΔGDP × 2000+				−0.077 (0.02)		
ΔGDP × Mid-Skill					−0.412 (0.05)	
ΔGDP × High-Skill					−0.428 (0.05)	
ΔGDP × Q2 Earnings						0.027 (0.02)
ΔGDP × Q3 Earnings						0.015 (0.02)
ΔGDP × Q4 Earnings						0.001 (0.02)
ΔGDP × Q5 Earnings						−0.031 (0.02)
R-Squared	0.001	0.003	0.000	0.000	0.002	0.003
N	4,575,704	4,575,704	4,575,704	2,555,948	995,963	3,269,512

Note: Dependent variable is change in real log hours worked. Sample held fixed for columns (1)–(3). Sample is lower in columns (4)–(6) due to missing variables. Standard errors clustered by worker. Years 1975–2020. Source: ASHE.

sive to aggregate shocks. When it comes to age, the patterns are different. The hours of the youngest workers are actually the least responsive to aggregate shocks. Older workers, and particularly those aged over 55, see the most responsiveness of hours to aggregate shocks. In column (3), we see that as with earnings, public sector workers are shielded from changes in hours. However, union-covered workers' hours are more responsive to aggregate shocks. This makes sense if one considers that wage rigidities are particularly binding for this group, so hours adjustments become more attractive for employers faced with shocks. For firm size in column (4), we see the same patterns as when the outcome variable was weekly earnings, with those at larger employers seeing a lower responsiveness. In column (5), we see that low skilled workers are the most responsive in terms of hours. As the sample for the final result includes only the Covid-19 recession, we again stress caution when interpreting these estimates. Due to the furlough scheme, discussed in detail in Appendix D, hours data from 2020 are likely to be less reliable than for other years.

4.2 *The 2020 recession*

The data used for the UK are uniquely up to date. This enables us to investigate patterns in the most recent recession. As shown in Section 3 of this paper, the Covid-19 shock has resulted in substantial wage drops for many workers. Here, we investigate this in more detail, focusing on the size of the falls relative to previous recessions.[17]

To directly compare the response of earnings in the Covid-19 recession to those of previous shocks, in Figure 10 we plot the patterns predicted from the estimates reported in Table 3 for a drop in GDP of 7.4%. This is the annual change in the monthly GDP index from March 2019 to March 2020 (noting March is the month just prior to the earnings data being reported). It is also close to the overall fall in GDP for the calendar year 2020, which was 9.9%. These are given in the "Predicted Covid-19 effect" bars.[18] We then compare these with the actual outcomes from the data, indicated in the figure as "Actual Covid-19 effect."[19] Despite the very different causes of the Covid-19 recession, in terms of earnings the relative size of the effects are very close to what would have been predicted given the size of the GDP shock and the historic beta estimates. Across all workers, the predicted effect on earnings is 2.8%, which is a little greater than the actual estimated effect of 2.3%. This broad similarity of previous shocks and the Covid-19 shock in terms of labor market effects has also been shown in survey data by Bell, Codreanu, and Machin (2020).

As in previous recessions, younger workers are the most exposed to the Covid-19 shock in terms of earnings, followed by the very oldest workers. Higher earners are less exposed, with the Covid-19 recession seeing a steeper gradient across permanent

[17]The caveat to this section is that firm nonresponse for this year was higher than in previous years, meaning the sample is smaller. Nonresponse is not likely to be random, and a reasonable assumption is that firms who experienced a greater negative shock were less likely to respond.

[18]The qualitative patterns from Table 3 and Table 4 hold with the latest recession excluded.

[19]These are obtained from a regression of wage changes on a dummy for 2020 (and interactions with the demographics).

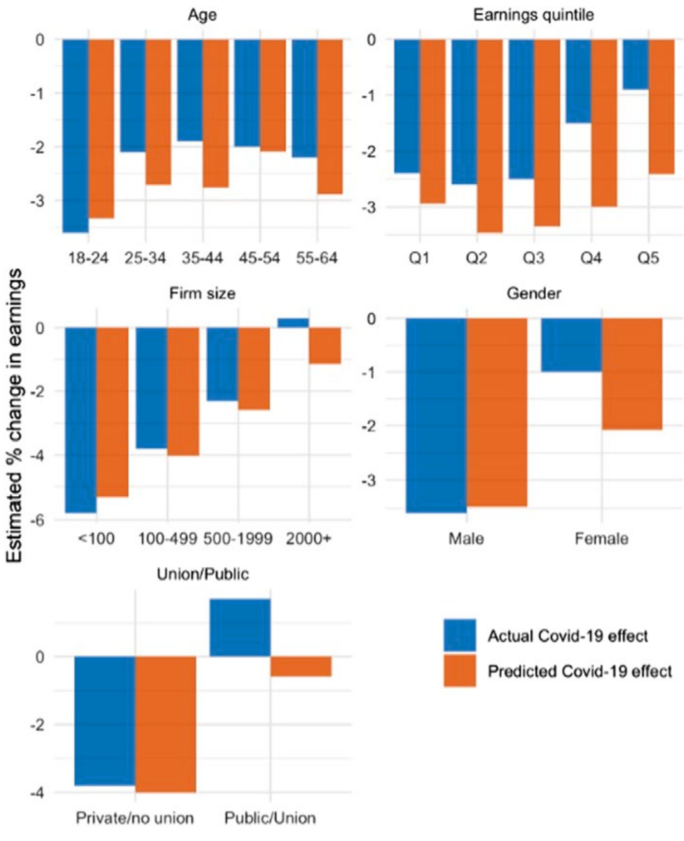


FIGURE 10. Predicted and actual Covid-19 earnings effects. Notes: Comparison of estimated actual Covid-19 effect on earnings and predicted effect using data 1975–2020, other than firm size, which uses 2002–2020. Assume a GDP drop of 7.4%, which is the annual change in the monthly GDP from March 2019 to March 2020. Source: Regression results reported in Table 3.

earnings than that found in previous years. Covid-19 has hit those in smaller firms the hardest, in line with our expectations based on previous shocks. Despite the literature showing the shock to have a disproportionate effect on female *employment* (Adams-Prassl, Boneva, Golin, and Rauh (2020) and Alon, Doepke, Olmstead-Rumsey, and Tertilt (2020)), we find that in terms of *earnings*, men experienced a larger shock. There are two possible explanations for the difference. First, we are examining *earnings* of continuing employees, so are not focusing on employment and our earnings data omit the impacts of job-loss. However, Bell, Codreanu, and Machin (2020) find little gender difference in the employment effect of the Covid-19 recession, so this may not be a major driver of these differences.[20] A second explanation might be that the prior literature tended to use online survey platforms like Prolific and Lucid, which while enabling a rapid response has some sampling issues in that they tend to oversample younger, female, educated employees. It is possible this generates issues around the impact of pandemic on these (or other) demographic dimensions. Resolving this question is clearly an important area

[20]This is unlike in previous recessions, where male workers experienced greater drops in employment.

of ongoing research, and something that further earnings, hours, and employment administrative and survey data can hopefully resolve.

As in previous recessions, those in the private sector and outside of union agreements are hard hit, with public sector unionized workers seeing wage increases relative to recent years.[21] While the cause of the 2020 recession is unique, in terms of how it is affecting the earnings of different workers, the qualitative patterns closely resemble those of previous recessions.

4.3 *Firm-level shocks, earnings, and hours*

Having explored the role of aggregate shocks, we now turn to the transmission of firm-specific shocks to workers. To do so, we run a series of earnings regressions, in which the measure of firm-level performance is log value added per worker, consistent with the existing literature. Concerns over measurement error and endogeneity lead us to report both OLS and a set of IV estimates. The results are shown in Table 5. Columns (1) to (4) use log weekly earnings as the outcome variable. Panel (a) shows the OLS estimates and panel (b) the IV estimates. In column (1), the instrument is the log of the average value added per worker among all the firms in each firm's 3-digit industry, excluding the firm's own measure. This leave-out mean specification is common in the rent-sharing literature and uses industry-level productivity shocks to instrument for firm-level productivity shocks. The instrument is strong, delivering an F-statistic of 35. The IV coefficient is 0.065, an order of magnitude higher than the OLS estimate of 0.007. This large rise in the coefficient when comparing OLS and IV is common in the literature. For example, Card, Devicienti, and Maida (2014) using matched worker-firm Italian data report an OLS elasticity of 0.008 and an IV estimate of 0.029. As this is the most common approach in the literature and we are able to use the largest sample for this instrument, we consider the IV estimate from column (1) as our baseline specification.

TABLE 5. Rent sharing estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS								
log(VAPW)	0.007	0.009	0.006	0.006	0.004	0.004	0.005	0.006
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Panel B: IV								
log(VAPW)	0.065	0.062	0.028	0.061	0.015	0.016	0.005	0.018
	(0.020)	(0.017)	(0.011)	(0.024)	(0.011)	(0.009)	(0.006)	(0.009)
N	597,943	331,296	486,088	281,996	596,515	331,148	485,511	281,934
F-Stat	35.12	43.75	63.84	14.97	34.95	43.77	65.54	14.96
Hansen p				0.672				0.645

Note: Dependent variable is log weekly earnings in columns (1)–(4) and log weekly hours in columns (5)–(8). All specifications include firm-worker match fixed effects. Standard errors clustered by firm. Source: ASHE/ARD/FAME.

[21] These responses are calculated by summing the relevant coefficients. This pattern likely in part reflects public pay restraint since the Great Recession, meaning low increases in public pay in the early 2010s.

In column (2), an alternative instrument is used. We use the value-added estimate from FAME data to instrument our primary measure of value added, which comes from the ARD. The sample is far smaller here, as our matched FAME sample contains only a subset of firms in the ARD. If measurement error is indeed an issue, and we assume the measurement error in the ARD and FAME are uncorrelated, we can use the FAME-based measure as an instrument to remove the measurement error in the ARD-based measure. The IV estimate however is strikingly similar to that of column (1), at 0.062. This is consistent with measurement error being the issue that is addressed via instruments of these types, rather than endogeneity.

In column (3), we use the lagged value added per worker as an instrument. This delivers a lower point estimate, of 0.028. Once again however, the qualitative pattern of the IV estimate being substantially larger than the OLS estimate is maintained. In column (4), we jointly include all three instruments. Hansen's overidentification test delivers a p-value of 0.672, so we cannot reject the null that the overidentification restrictions are valid. The estimated coefficient is 0.061, close to our baseline estimate.

Columns (5)–(8) replicate columns (1)–(4) but with hours as the outcome. While the IV estimates are imprecisely estimated, and often insignificantly different from zero, the point estimates suggest that perhaps a quarter of the response of weekly wages to firm-level shocks is coming through an hours response. The ratio of the hours and earnings effects is close to that which we found when estimating responses to aggregate shocks above.

Overall, the results suggest that wages are responsive to firm-level shocks. IV estimates are significantly larger than the OLS estimates, and the evidence suggests that this is a result of measurement error in the firm-level measure of value-added per worker. Even though the IV estimates are larger, they are substantially smaller than the elasticity estimates for aggregate-level shocks. However, the extent to which workers are exposed to aggregate shocks and firm-level ones depends on both the size of the estimated elasticity and the variance in the size of the shock. Over the sample period, the standard deviation of the change in GDP is 2%, while the within-firm standard deviation of the log of value-added per worker is between 0.28 and 0.44 depending on the firm-level data source. While recognizing that firm-level data tends to be measured with substantial error, the estimates suggest that a standard deviation fall in GDP causes wages to fall by 0.8% (or 1.6% with a dynamic specification), and a standard deviation fall in firm-level value-added causes wages to fall by 2.3%.

Finally, we examine the heterogeneity in the wage responsiveness to firm-level shocks matching the aggregate analysis conducted above. We report IV estimates using the 3-digit industry instrument as this is one of the most common approaches used in the literature. The results are shown in Table 6, while in Appendix D we report equivalent tables using each of the alternative instruments and all instruments combined (Tables D5–D7). Interestingly, the patterns are substantively different to those for aggregate shocks. While women are again less exposed (and the estimated coefficient is significantly more negative in some of the IV specifications), exposure is higher for those outside the youngest age bracket, for those in larger firms (though the magnitude of differences is small), and for the more skilled. Kline, Petkova, Williams, and Zidar (2019)

TABLE 6. Log earnings firm-shock heterogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)
log(VAPW)	0.066	0.039	0.068	0.057	−0.025	0.063
	(0.027)	(0.021)	(0.020)	(0.021)	(0.036)	(0.020)
log(VAPW) × Female	−0.003					
	(0.027)					
log(VAPW) × 25–34		0.035				
		(0.002)				
log(VAPW) × 35–44		0.039				
		(0.002)				
log(VAPW) × 45–54		0.037				
		(0.002)				
log(VAPW) × 55–64		0.023				
		(0.002)				
log(VAPW) × Union			−0.002			
			(0.001)			
log(VAPW) × 100–499				0.002		
				(0.001)		
log(VAPW) × 500–1999				0.006		
				(0.002)		
log(VAPW) × 2000+				0.009		
				(0.002)		
log(VAPW) × Mid-Skill					0.022	
					(0.002)	
log(VAPW) × High-Skill					0.029	
					(0.002)	
log(VAPW) × Q2 Earnings						0.003
						(0.001)
log(VAPW) × Q3 Earnings						0.008
						(0.001)
log(VAPW) × Q4 Earnings						0.016
						(0.002)
log(VAPW) × Q5 Earnings						0.029
						(0.002)
N	597,943	597,943	597,943	597,938	203,311	429,387

Note: Dependent variable is real log weekly earnings. Standard errors clustered by firm. Years 2002–2014. Estimation is by match fixed-effect IV, instrumenting log value-added per worker (VAPW) with log(VAPW) in the same 3-digit industry (column (1) of Table 5). Source: ASHE/ARD.

show that men and high earners capture more of the gains to a patent-induced shock to firm-level labor productivity. Card, Devicienti, and Maida (2014) find that rent-sharing is higher for workers in larger firms (more than 100 employees) and marginally higher for unionized workers and women. In contrast to our results on skill and those of Kline et al., they find larger effects for blue-collar workers.

5. Conclusions

In this paper, we use an employer-based survey of earnings and hours to set out the key patterns in UK earnings dynamics from 1975 to 2020, with a particular focus on the recent Covid-19 shock. Consistent with previous work, we demonstrate a significant rise in earnings inequality throughout most of the period, with a leveling off in more recent years. The distribution of earnings changes in the UK exhibits substantial and growing deviations from log normality, with a strongly pro-cyclical skewness and a gradual rise in kurtosis across the period of study. In terms of intragenerational mobility across the earnings distribution, the older a worker gets the more fixed their position is. We find some evidence that 10-year mobility has fallen over time.

Investigating the effect of aggregate shocks, we find that earnings and hours are procyclical. There are substantial asymmetries in both, with dampened earnings adjustment in recessions and hours adjustments occurring almost entirely in recessions. Exposure to aggregate shocks is falling in age, firm size, skill level, and permanent earnings, and is lower for unionized and public sector workers. Turning to the Covid-19 shock, the patterns of heterogeneity in earnings changes early in the 2020 recession are qualitatively the same as in previous recessions, despite the different nature of the shock. Using the last 20 years of data, we also find a significant role of firm-level shocks in determining earnings given the size of within-firm variation in such shocks. In contrast to aggregate shocks, exposure is rising in age, firm size, skill level, and permanent earnings, and shows no difference between unionized and non-unionized workers.

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