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

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Appendix A: Background on the UK labor market

A.1 *Macroeconomic trends*

Figure A.1 shows the evolution of annual real GDP growth, inflation, and unemployment over the period, which saw four recessions (1980–1981, 1990–1991, 2008–2009, and 2020). The first 5 years of the period was a particularly volatile period. The "winter of discontent" in 1978–1979 saw widespread industrial action, with the government clashing with unions in an attempt to bring high inflation under control (Hay (2009)). The outcomes of these wage negotiations and the double-digit inflation rates combine to deliver unusual and highly unstable wage patterns over the period, which will be evident in the wage data presented in Section 3.

To combat inflation, in 1979 Margaret Thatcher's newly elected Conservative government tightened monetary and fiscal policy (Backhouse (2002)). This led to the 1980–1981 recession, which was swiftly followed by high unemployment for most of the 1980s, peaking at 12% in 1984. Sterling appreciated significantly, and the manufacturing sector was struck particularly severely. Following a sharp rise in union power throughout the preceding decade, Thatcher's government was successful in reducing the power of unions (Machin (2000), and Blanchflower and Bryson (2008)).

The mid to late 1980s saw high economic growth and rising inflation. Low interest rates led to a boom in the housing market and income tax cuts helped fuel an increase in consumer spending. In 1990, the boom turned to bust, the economy again entering a recession. This second recession was shallower than that of 1980–1981, with unemployment peaking at around 10% between 1992 and 1994. Unlike the previous crisis, house prices crashed, losing 10% of their value in 1990 (Pintér (2019)).

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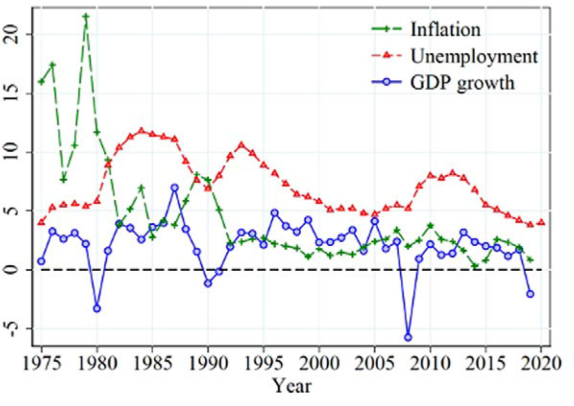


FIGURE A.1. Macroeconomic trends 1975–2020. Notes: GDP growth given in real terms. GDP growth and unemployment rate refer to Q1 of each year, inflation to Q2. Growth rates for year t refer to changes from t to $t+1$. Source: Office for National Statistics, Federal Reserve Bank of St. Louis.

The “great moderation” period from the early 1990s into the late 2000s is characterized by low inflation, falling unemployment, and steady growth. Relative to the US and many other European countries, the UK did not experience an early 2000s recession. Throughout the period, output per hour worked grew steadily at a rate of approximately 2% (Herz (2020)).

The UK did however experience a sharp downturn in the Great Recession of 2008–2009. The economy contracted by over 5%, representing the deepest recession since the Second World War. Given the scale of this recession, Figure A.1 shows the employment effects to be relatively mild in the short term. While employment held up, wages and productivity stagnated in the decade that followed (Herz (2020) and Crawford, Jin, and Simpson (2013)). During the 2010s, there was a substantial fiscal tightening. The Conservative government’s austerity programme consisted of sustained reductions in public spending and tax rises (Fetzer (2019)). This included cuts to public services and a public sector pay freeze from 2011 and 2013, followed by commitments to wage restraint since then (Cribb, Emmerson, and Sibieta (2014)).

At the time of writing, we are still experiencing the 2020 Covid-19 recession. In terms of aggregate growth, the UK has been particularly negatively affected. Figure A.1 shows data up to Q1 2020, at which point the fall looks relatively mild. In Q2 2020, real GDP was 21.7% lower than it was a year earlier, dwarfing all previous downturns. For 2020, GDP declined by 9.9%—one of the largest drops across the OECD. As elsewhere, the government has responded by introducing unprecedented labor market support programmes. Most relevant to the current paper is the furlough scheme, in which the government provided employers with 80% of employee wages, on the condition that the worker was not performing any work at the time.

Another key part of the story of the UK’s economy over the period is migration. From 1975–1995, net migration to the UK was stable. Since then, and particularly since 2004, net migration has increased. In the years that followed the expansion of the EU in 2004, the UK saw high immigration from Central and Eastern Europe (Dustmann and Frattini (2014)). Despite this, the share of foreign-born population in the UK is comparable to that of other European countries (Eurostat (2021)). Since the EU referendum in 2016, the number of EU workers moving to the UK has fallen, but the number of non-EU workers has risen. Kerr, Kerr, Özden, and Parsons (2017) have shown that the UK is a particularly attractive destination for high-skilled migrants. More recent work has used tax data to show that almost all (85%) of the growth in the UK top 1% income share over the past 20 years can be attributed to migration (Advani, Koenig, Pessina, and Summers (2020)). Looking ahead, the UK's exit from the EU is likely to change the UK's labor market substantially. European immigrants constitute a large share of workers, in particular sectors and occupations, and any worsening in the UK's access to international markets may have substantial effects on some workers.

In terms of labor force participation, the UK has not seen the long decline found in the US (Krueger (2017)). Over the period under study, female labor force participation increased from 55% to 72%. The gender pay gap, as in the US, has been falling over the period (Petrongolo (2019)). Until very recently, part-time work has been rare among male workers, so the part-time pay penalty plays an important role. Manning and Petrongolo (2008) report the gap to have widened greatly over the period of study, and that it can be mostly explained by worker characteristics and occupational differences.

The UK has particularly strong geographical inequalities. Many of the highest-skill jobs, particularly in professional services, are found in London and the South-East. Previous industrial heartlands of the Midlands, South Wales, the North-West, and the North-East have lower wages and high unemployment. While narrower today than in the 1980s (Dolton, Rosazza-Bondibene, and Wadsworth (2011)), there remain persistent differences in wages and employment by area.

A.2 *Labor market institutions*

Turning from macroeconomic trends to labor market institutions, the UK is typically thought to occupy a relatively distinct space between US and European-style labor markets. Compared to elsewhere in Europe, UK workers are provided little employment protection. Summarizing regulation of individual worker dismissals, the OECD scores only the US, Switzerland, and Canada as offering less protection. A key labor market policy shift came in 1999 with the introduction of a national minimum wage. Initially, this was low by international standards. It has risen substantially in real terms and for most workers in 2020 was 60% of the median full-time hourly wage (Dolton, Bondibene, and Wadsworth (2010); LPC (2020)). As a proportion of median full-time wages, it is now among the highest in the world.

As discussed in the previous section, aggregate union density began a long downward trend from 1980 onward, a trend that occurs across sectors but most notably in manufacturing. The public sector has remained highly unionized despite the decline in the private sector. While union density has fallen dramatically, the decline in coverage of union-negotiated collective agreements has been significantly less precipitous (Bryson and Forth (2011)).

The labor market has seen a rise in the share of workers in alternative working arrangements. Most prominent is the rise in self-employment, particularly the solo self-employed (Boeri, Giupponi, Krueger, and Machin (2020)). As of 2019, the self-employed constitute 15% of aggregate employment, and recent survey evidence suggests that the Covid-19 crisis has struck the self-employed particularly hard (Blundell, Machin, and Ventura (2020)). The period has also seen growth in Zero Hours Contracts—employment contracts in which a worker is not guaranteed any hours and is only paid for work carried out. Datta, Giupponi, and Machin (2019) estimate their prevalence to be at 2.7% of workers. These workers are covered by many of the same regulations as permanent employees. Unlike Italy, France, and Spain, in the UK we have not seen extensive use of temporary contracts among workers early on in their careers. Medina and Schneider (2018) estimate the UK's shadow economy to be under 10% of total employment, small by global and European standards.

Appendix B: Data appendix

B.1 *Additional information on ASHE*

As discussed in Section 2, the main outcome variable of interest is weekly earnings. This data misses out some important components of income. Most importantly, as pay refers only to pay received within a particular reference period, for the most part this will miss bonus pay. These payments are in theory captured by asking employers to proportionately allocate any incentive or bonus payments made outside the survey week, provided the incentive was related to work in that week. However, a large share of bonuses do not appear to be captured in the weekly data. Bell and Van Reenen (2014) show that bonuses are an important component of top-tail inequality. In line with that paper, we will show how using the annual earnings measure, which does include bonuses, affects the earnings distribution. ASHE includes only cash payments, so any remuneration paid using restricted shares and option grants will be excluded from the data. Again, these are likely to be more important toward the very top of the distribution.[1]

The hours data in ASHE refer to the total hours the employee worked in the reference week, according to the employer. The hours variable is more accurate for hourly-paid workers as is typical in administrative employer-reported hours data, and there is significant bunching at a handful of discrete thresholds representing standard contracts. For some workers, these will not reflect the true hours worked over the week. As discussed in Ritchie (2005), hours for nonmanual workers are consistently lower in this data than as reported in household surveys.

The worker's three-digit occupation code is also available, along with age and sex. This is used to assign a skill level to each worker using the UK Government's skill level classifications.[2] This is possible only for years 2011 onward. Employer identifiers, which

[1] Studies focusing on the top end of the earnings distribution tend to use the Survey of Personal Incomes (SPI), which provides a more complete picture. This survey does not contain a panel dimension, so is not appropriate for this paper.

[2] Home Office Immigration Rules Appendix J: Codes of Practice for Tier 2 Sponsors, Tier 5 Sponsors, and employers of work permit holders.

allow the linking of other ONS and external data are available from 2002 onward.[3] We also use a variable indicating whether or not a worker's wage is covered by a collective agreement, which we use as a measure of unionization.[4] There is also an indicator for whether or not a worker is in the public sector.

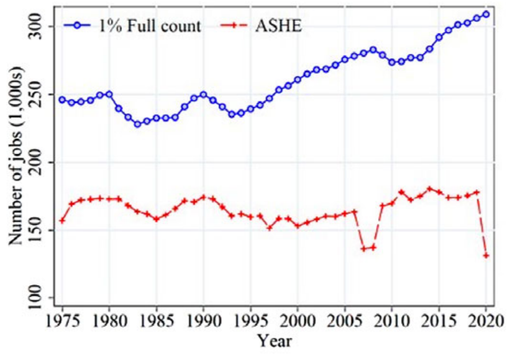
While the information in ASHE is thought to be of exceptionally high quality, not all workers are eventually included in the data, although all workers in the sample frame are considered. First, employees that work at businesses outside of the interdepartmental business register (IDBR) are excluded as they cannot be identified in the tax administration records. These are typically very small businesses who fall below the Value Added Tax (VAT) threshold. Currently, the threshold is set to a turnover of GBP 85,000 (USD 110,000). Relatedly, employees who earn below the National Insurance Lower Earnings Limit (LEL) are not subject to PAYE tax withholding, so will not be in the PAYE system. The current LEL is set to 120 GBP, or approximately 150 USD per week. This means that a number of the very lowest-paid workers are omitted from the survey. A minimum-wage earner working 15 hours per week in the UK makes 130 GBP, so the majority of missing workers will be those working fewer than 15 hours a week on the minimum wage. This is a small group, and will disproportionately be made up of women, who are more likely to work part-time. The ONS estimates that biases caused by omitting these missing firms and employees are likely to be small, though it is difficult to precisely quantify their extent. Workers falling below the LEL are not necessarily excluded. As Ritchie (2005) points out "because tax records are held over, even if no tax is paid in a particular year, rather more are included than might be expected."

The two issues above are due to the administrative process of constructing the sampling frame. However, a comparison of sample sizes in ASHE to employment count estimates suggests there to be nonnegligible nonresponse issues. Figure B.1 compares the number of jobs appearing in ASHE to 1% of the estimated aggregate number, provided by the ONS and drawn from a variety of data sources. Between 30% and 40% of jobs are missing for most periods. We see that the share missing is broadly stable from 1975–1996, then falls in the late 1990s before stabilizing again from 2000. It is not clear why this fall in coverage occurs, and this pattern means we must be cautious when interpreting changes, which occur in the mid to late 1990s.

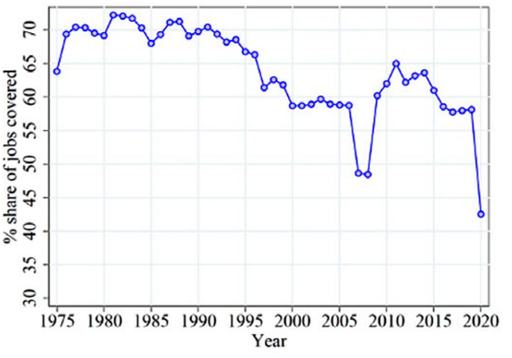
There are two points at which coverage falls below 50%. The first come in 2007 and 2008. In these years, there was a temporary reduction in the sample size, which the ONS stated was due to "work priority" reasons. Reductions were "targeted on those industries that exhibit the least variation in their earnings patterns." This means that we should

[3] The "entref" ID variable refers to the "enterprise," which is close to the typical definition of a "firm" and is the standard grouping of organizations used by the ONS. Formally, an enterprise is the smallest combination of legal units (based on VAT and PAYE records) that is an organizational unit producing goods or services, benefiting from a degree of autonomy in decision-making, especially for the allocation of current resources. Enterprises carry out one or more activities at one or more locations and may be sole legal units.

[4] For those covered by collective agreements at the national, sectoral, or regional level, this is coded as 1. For those covered by collective agreements at the organizational or workplace level, this is coded as 0. The share of workers covered by unions according to this variable declines from just over half in 1975 to around a quarter in the most recent years, in line with government statistics on trade union membership.



(A) ASHE COUNTS AND TOTAL JOBS



(B) % SHARE COVERED BY ASHE

FIGURE B.1. ASHE coverage. Notes: 1% full count is total count of employee jobs according to ONS. Includes multiple job holders. Panel (b) is derived from the two series in panel (a). Source: ASHE, ONS using Employer surveys, Labour Force Survey and administrative sources (A01 Labour market statistics summary data tables).

interpret the estimates for these 2 years with caution, particularly when looking at earnings changes. The second comes in 2020, which is attributable for the timing of the survey, during the first lockdown of the Covid-19 crisis. The disruption caused by the crisis likely led to a large number of firms not entering their information.

There are two main reasons for nonresponse. First, the employee has moved employers between the point at which employers are identified in the tax data and the point at which the survey is sent out (Ritchie (2005)). It can also be that employers have retained previous workers in their PAYE records, despite the fact that they no longer work there. Bird (2004) reports that in 2003, 12% of responses stated that the employee in question had left the business. This means that job movers are undersampled in ASHE. The second type of nonresponse is that even though businesses are legally obliged to comply, it is not clear how well this is enforced in practice. It is possible to identify in the data a small number of cases, which are strongly suggestive of complete firm nonresponse. Ritchie (2005) estimates that return rates on the ASHE forms are typically 95%.[5]

When an individual is missing, it is not possible to observe why this is. This makes the data set inappropriate for studying movements into or out of employment. Missing individuals could be unemployed, have left the labor market or migrated abroad, be self-employed or be missing due to the reasons described above. Missingness is nonrandom, with those who change jobs more frequently more likely to become missing, along with women, low earners, and workers at smaller firms.

Up to and including 2003, very little changed in the methodology underlying the survey. In 2004, the NES formally became ASHE. The most important change for the current paper is that the latter attempts to improve on the tracing of workers who change jobs just before the survey period. Originally, the NES finds workers from tax records in January or February, and bases their form send-out addresses on this. From 2004, ASHE

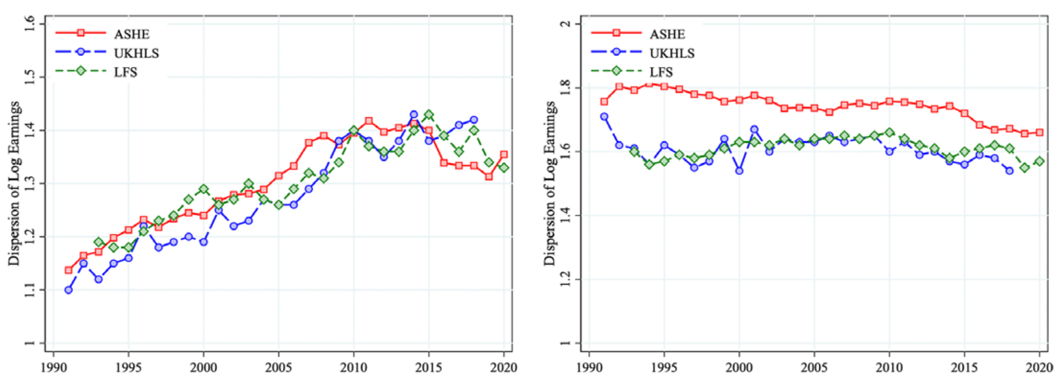
[5]Limited weights are available for the most recent years, but for consistency over time we do not use these.

used an additional later date to identify new leavers/joiners. ASHE also included more small businesses, which did not operate within the standard tax withholding (PAYE) system. This was done using a supplemental survey. Finally, there is some imputation of aspects of earnings and hours in the data set, but this does not apply to our main earnings and hours variables. Given these changes, we ought to be cautious when interpreting any trend breaks around this time.

B.2 *Representativeness of ASHE data*

In light of the issues raised above, we are interested in assessing the representativeness of the ASHE data. To do this, we can compare the level and trends in earnings inequality with two alternative household surveys for the second half of the sample period. The Labour Force Survey (LFS) has data on gross weekly wages from 1993–2020 and is a representative cross-section random sample of the UK population, equivalent to the US Current Population Survey. There are on average about 34,000 wage observations per year for those aged 25–55. The UK Household Longitudinal Study (UKHLS) is a longitudinal study, which has data on gross monthly wages from 1991–2018. The sample was boosted in 2009 with the addition of a large number of new households. There are around 3700 wage observations per year for those aged 25–55 prior to 2009, and around 11,400 per year subsequently. For each of the survey data sets, we impose the same sample restrictions as those used in the main paper for the ASHE data.

Figure B.2 shows the 90–10 log differential for men (panel A) and women (panel B) using the three different sources. For men, there is a high correlation between the level and trend in earnings inequality across all three data sets. There is no obvious evidence to suggest that ASHE is providing a misleading picture of the earnings distribution for men over this sample period. For women, the trends are very similar across the data sets (except for a sharp drop in inequality reported by UKHLS for the first 2 years, which is not reflected in ASHE). However, the level of inequality is persistently higher using ASHE



(A) MALE (B) FEMALE

FIGURE B.2. Comparison of ASHE Inequality Measures with Survey Data. Source: ASHE, Labour Force Survey and UK Household Longitudinal Survey.

TABLE B.1. Descriptive statistics for LX sample by year.

(A) Earnings and demographics

Year	Obs	Fem inc	Male inc	Female %	Age 25–35%	Age 36–45%	Age 46–55%
1975	37,023	326	609	31.5	40.3	38.2	21.4
1980	42,873	335	637	36.2	41.3	39.4	19.3
1985	48,785	379	700	38.0	39.6	41.8	18.5
1990	57,790	485	843	41.8	41.4	41.1	17.5
1995	55,256	523	847	43.9	40.7	38.8	20.5
2000	50,080	576	936	47.1	35.6	44.5	19.9
2005	53,395	660	1039	49.7	32.2	46.1	21.7
2010	53,537	677	986	50.9	32.8	42.1	25.0
2015	34,480	642	896	51.6	35.0	39.3	25.7

(B) Earnings percentiles

Year	Percentile 1	5	10	25	50	75	90	95	99	99.9
1975	97	159	222	362	499	647	814	935	1278	1995
1980	78	141	201	358	505	658	840	986	1405	2177
1985	76	144	219	378	539	721	948	1129	1657	2895
1990	87	175	264	432	631	862	1139	1380	2198	4289
1995	84	177	265	435	637	887	1168	1413	2194	4222
2000	94	190	276	457	677	960	1280	1578	2554	4693
2005	116	214	299	498	738	1062	1442	1773	3032	5681
2010	121	215	303	495	727	1042	1395	1724	2752	4917
2015	115	209	286	464	676	965	1298	1572	2429	4149

Note: Summary statistics for the LX 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.

data compared to the other surveys. This is entirely in the P50–P10 level as the P90–P10 show very similar levels and trends. The key reason for the difference is that although ASHE theoretically does not include workers below the PAYE tax withholding threshold, in practice some of these workers are included in firm responses to ASHE. Since these are all low-wage workers, this tends to raise the P50–P10 ratio.

It is more difficult to examine how ASHE compares to other data sets in terms of wage changes. LFS is primarily a cross-section survey and UKHLS has a small sample to examine wage changes. Indeed, ASHE is the only realistic data set that can be used in the UK to estimate measures of earnings dynamics that require accurate earnings data and large samples. We have however used the UKHLS to estimate the skewness of 1-year wage changes over the period 1992–2018. Over this whole sample period, the estimate of Kelley skewness is 0.04 for men and 0.07 for women. This is close to the estimates from ASHE shown in Figure 6 and matches the slightly higher estimate for women than for men.

TABLE B.2. Descriptive statistics for H sample by year.

(A) Earnings and demographics

Year	Obs	Fem inc	Male inc	Female %	Age		
					25—35%	36–45%	46–55%
1980	27,967	357	656	33.3	35.5	42.6	21.9
1985	34,779	403	727	35.7	33.3	45.7	21.0
1990	40,057	522	877	38.5	35.1	44.9	19.9
1995	41,210	559	891	41.8	35.0	42.0	23.0
2000	36,212	608	969	45.2	30.2	47.5	22.3
2005	36,467	697	1090	48.1	25.6	49.9	24.5
2010	31,031	716	1053	49.6	26.7	45.2	28.1
2015	24,223	685	950	50.2	28.1	42.3	29.6

(B) Earnings percentiles

Year	Percentile									
	1	5	10	25	50	75	90	95	99	99.9
1980	93	160	235	389	534	685	866	1017	1431	2283
1985	89	163	255	408	574	753	984	1169	1695	2811
1990	108	210	311	474	681	906	1190	1440	2277	4189
1995	102	211	308	474	684	934	1222	1472	2266	4280
2000	117	222	313	494	723	1006	1321	1621	2562	4654
2005	138	247	340	542	794	1119	1499	1834	3111	6076
2010	145	248	346	537	787	1104	1475	1817	2878	4821
2015	141	243	332	507	729	1022	1350	1639	2509	4330

Note: Summary statistics for the H 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.

B.3 *Additional information on firm-level data*

As discussed in Section 2, we obtain firm-level data from two source: ARD and FAME. ARD data are directly matched by ONS. In contrast, the match between FAME and ONS data is imperfect. Matching has been performed via a lookup table held by the ONS, which contains enterprise reference (ONS)-company number (FAME) links for 2014–2018. For years prior to this, we backfill using the most recent enterprise reference match available. This should detect firms whether they survive to 2014 or not, though coverage becomes less reliable for earlier years. This is exacerbated by older extinct firms being dropped from the FAME database.

Companies included in FAME may be subsidiaries of one another, or part of a parent group. In these cases, the FAME company number matches to multiple enterprise references. When this occurs, we check the population and turnover figures against the Business Structure Database (BSD),[6] the main business register. This allows us to identify the most likely matches in cases where there is ambiguity. This also helps exclude

[6]Office for National Statistics. (2019). Business Structure Database, 1997–2018: Secure Access. [data collection]. 10th Edition. UK Data Service. SN: 6697, http://doi.org/10.5255/UKDA-SN-6697-10.

incorrect matches in the early part of the sample. Relative to the ARD, the disadvantage is that despite best efforts, there will be some incorrectly matched firms. For this reason, we use ARD as our main source of firm-level information and will use FAME as an instrument, to be discussed below.

Table B.3 shows the number of firms and workers in our worker-firm match sample, along with summary statistics at the firm level. Panel (a) shows this for the ARD. We see that between 31% and 40% of workers are matched to firm-level value-added measures

TABLE B.3. Descriptive statistics for firm-match samples by year.

Year	Firms	Workers	% Match	Employees	VAPW
			(A) ARD		
2002	10,176	53,855	38.0	522	36.3
2003	9749	54,634	38.0	583	36.5
2004	10,001	54,958	38.2	596	41.5
2005	9750	56,140	37.2	612	44.2
2006	8561	47,414	31.2	653	44.8
2007	8465	40,959	32.1	682	50.1
2008	8011	43,432	34.1	819	54.0
2009	9550	71,913	46.1	992	50.6
2010	8554	69,747	44.2	1045	55.7
2011	8950	72,948	44.1	1010	55.3
2012	9124	72,359	45.5	1026	56.8
2013	9115	72,954	45.5	1032	59.8
2014	9245	75,485	45.6	1046	63.8
			(B) FAME		
2002	4284	21,934	15.5	629	29.3
2003	5305	32,805	22.8	765	31.6
2004	5204	35,379	24.6	835	33.7
2005	5279	38,267	25.3	857	36.0
2006	5475	40,360	26.6	890	37.4
2007	5160	34,069	26.7	922	40.4
2008	5230	34,711	27.3	942	40.1
2009	7181	45,657	29.3	764	40.5
2010	8829	51,042	32.3	706	42.6
2011	9018	54,716	33.1	725	43.0
2012	9390	56,069	35.2	728	44.3
2013	9942	58,071	36.2	698	45.1
2014	10,324	59,825	36.1	698	46.3
2015	10,551	58,265	35.6	702	47.2
2016	10,306	55,858	35.1	706	48.2
2017	10,020	54,412	34.0	693	49.0
2018	10,379	53,605	34.2	673	50.0

Note: Number of matched firms and workers by year for ARD in panel (a) and FAME in panel (b). Employees and value added per worker refers to mean number of employees and mean value added per worker at the firm level in the matched sample. % match figure includes all workers with nonmissing earnings in the denominator, including public-sector workers. Source: ASHE, ARD, FAME.

TABLE B.4. Predictors of matching to firm data.

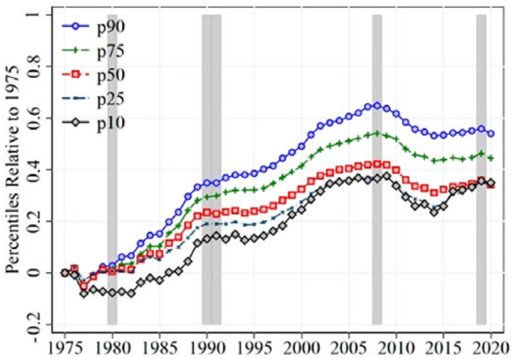
	(1) ARD	(2) FAME
Female	−0.070	−0.064
	(0.00)	(0.00)
(log)Earnings	0.008	−0.021
	(0.00)	(0.00)
Full-time	0.042	0.020
	(0.00)	(0.00)
Union	−0.006	−0.091
	(0.00)	(0.00)
Age:		
25–34	0.050	−0.038
	(0.00)	(0.00)
35–44	0.067	−0.029
	(0.00)	(0.00)
45–54	0.076	−0.024
	(0.00)	(0.00)
55–64	0.081	−0.028
	(0.00)	(0.00)
Firm size:		
100–499	0.442	0.399
	(0.00)	(0.00)
500–1999	0.727	0.442
	(0.00)	(0.00)
2000+	0.626	0.506
	(0.00)	(0.00)
Dep var mean	0.404	0.303
R-squared	0.399	0.299
N	1,947,882	2,587,482

Note: Outcome variable = 1 if worker in ASHE successfully matched to firm in ARD (column 1) or FAME (column 2). Column (1) includes years 2002–2014, column (2) years 2002–2018. Source: ASHE, ARD, FAME.

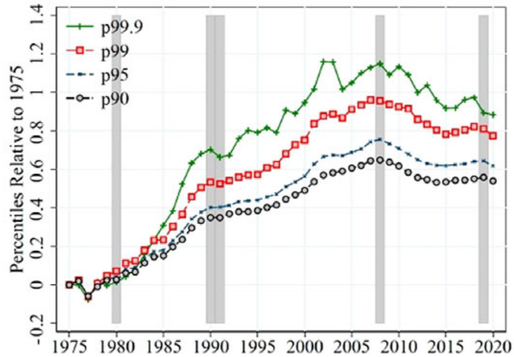
in the ARD.[7] Table B.4 shows that on average, matched workers are at larger employers than in the full sample, due to the nature of the ARD sample construction. They are also higher earning, older, more likely to be male and more likely to be full-time workers. Table B.3 panel (b) shows the equivalent information for FAME, which has lower match rates than the ARD. Matching is again nonrandom, as shown in Table B.4.

[7]A small number of public sector workers in quasi-public sector roles are matched successfully to the firm-level data.

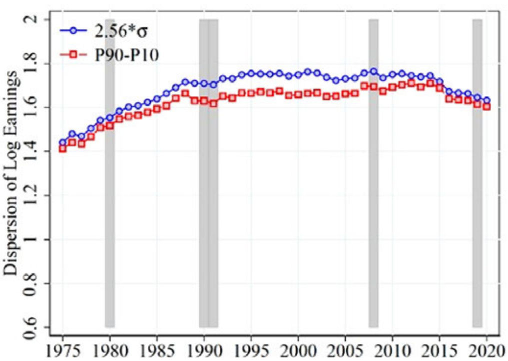
Appendix C: Additional tables and figures for Section 3



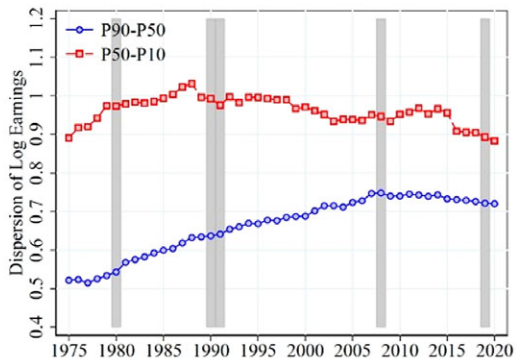
(A) Percentiles



(B) Top Percentiles

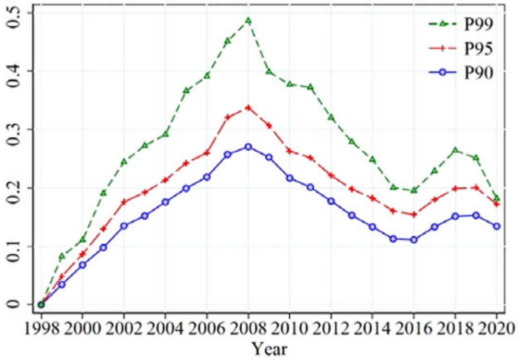


(C) Dispersion

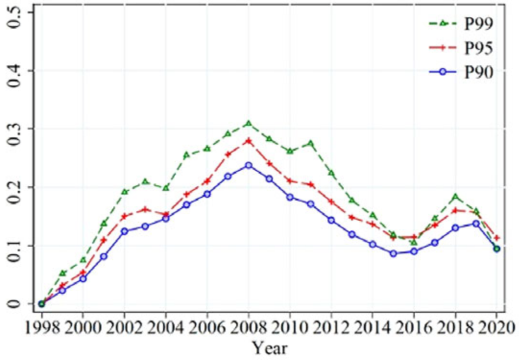


(D) Right & Left Tail Dispersion

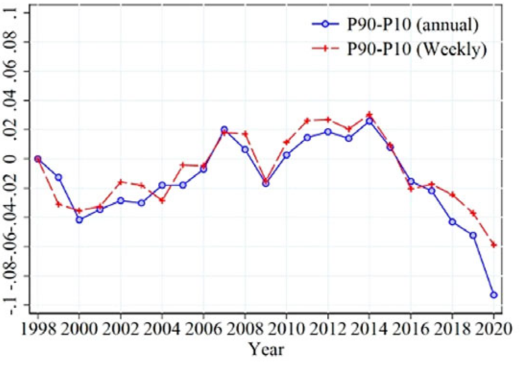
Figure C.1. Distribution of earnings in the population. Notes: Raw log earnings and CS sample. Shaded areas are recessions. $2.56 * \sigma$ corresponds to P90–10 differential for a Gaussian distribution. Male and female combined. Source: ASHE.



(A) TOP EARNINGS (ANNUAL)

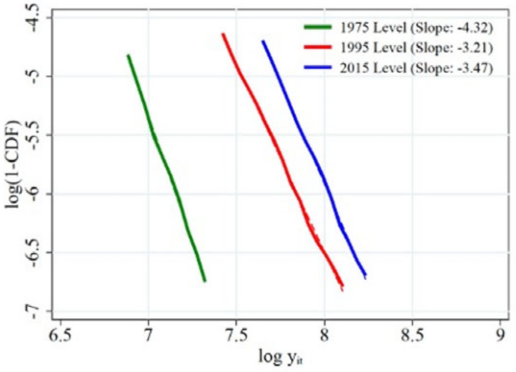


(B) TOP EARNINGS (WEEKLY)

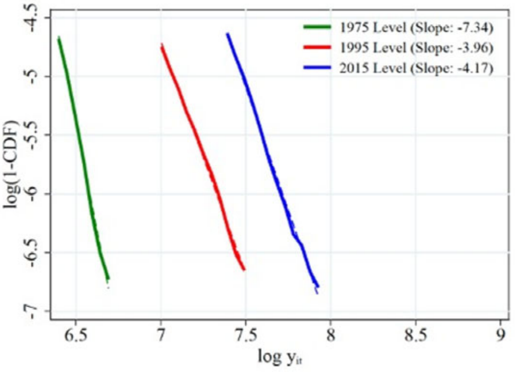


(C) P90--P10

FIGURE C.2. Comparison of annual and weekly earnings measures. Notes: Raw log earnings and CS sample. All percentiles normalized to 0 in 1998. Constrained to workers in the same job as previous year for both weekly and annual measure. Source: ASHE.

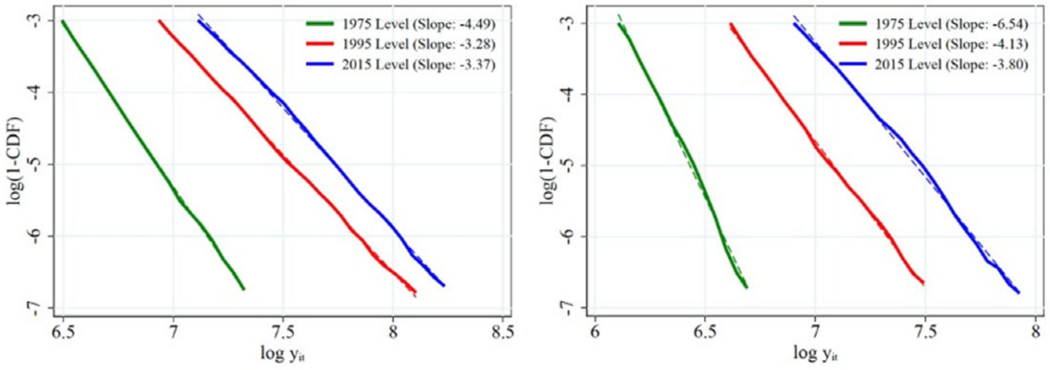


(A) MALE



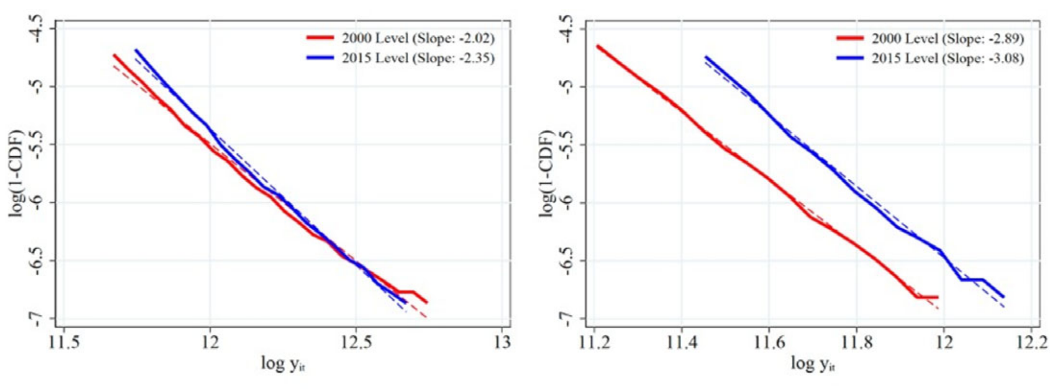
(B) FEMALE

FIGURE C.3. Top income inequality: Pareto tail at top 1%. Notes: Raw log earnings and CS sample. Top 0.1% omitted. Source: ASHE.



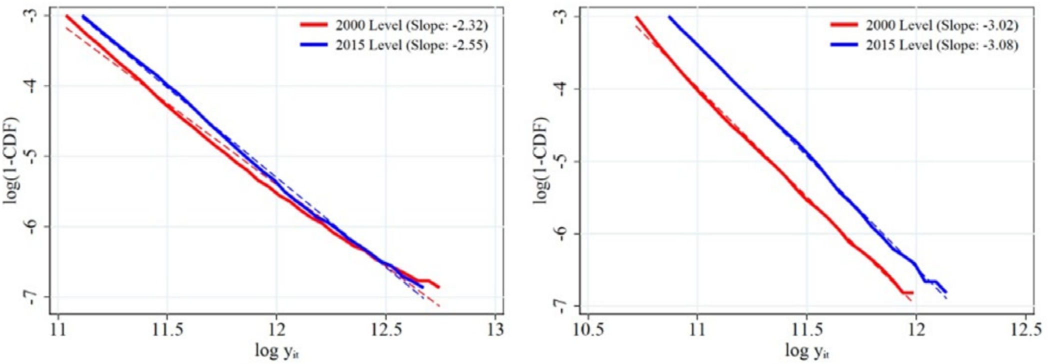
(A) MALE (B) FEMALE

FIGURE C.4. Top income inequality: Pareto tail at top 5%. Notes: Raw log earnings and CS sample. Top 0.1% omitted. Source: ASHE.



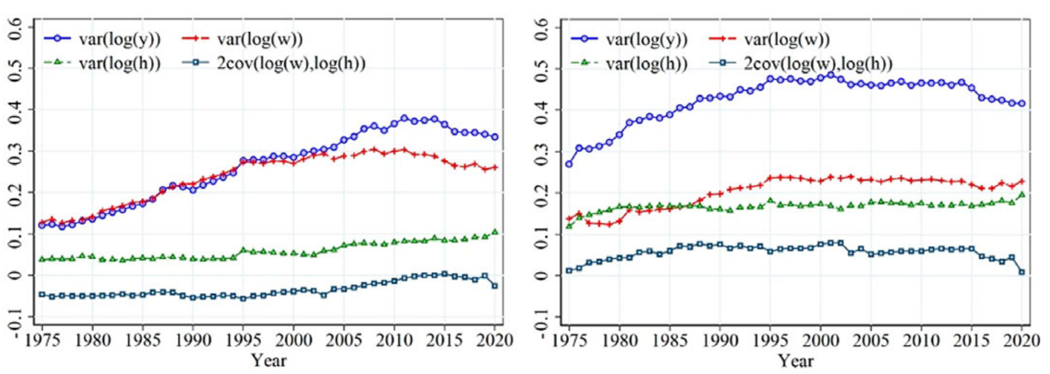
(A) MALE (B) FEMALE

FIGURE C.5. Top income inequality: Pareto tail at top 1% (Annual Earnings). Notes: Raw log earnings (annual) and CS sample. Top 0.1% omitted. Restricted to those in same job as previous year. Source: ASHE.



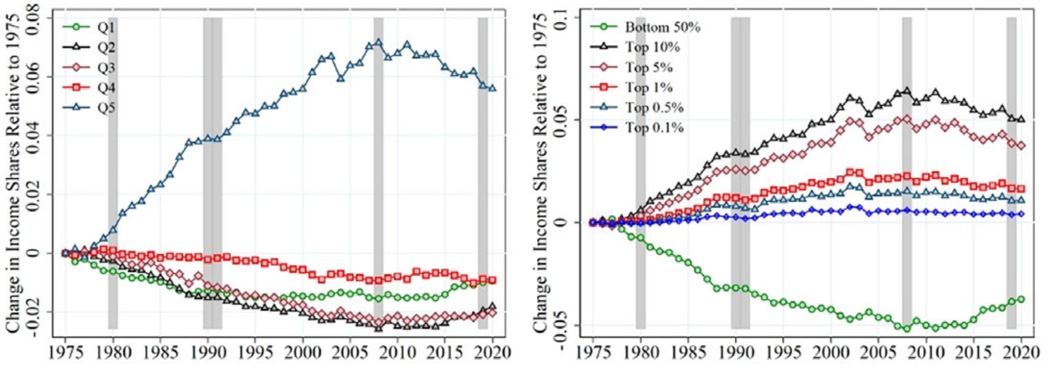
(A) MALE (B) FEMALE

FIGURE C.6. Top income inequality: Pareto tail at top 5% (Annual Earnings). Notes: Raw log earnings (annual) and CS sample. Top 0.1% omitted. Restricted to those in same job as previous year. Source: ASHE.



(A) MALE (B) FEMALE

FIGURE C.7. Hourly Wage and Hours Decomposition. Notes: Raw log earnings ($\log(y)$), log hours ($\log(h)$), and log hourly wages ($\log(w)$) and CS sample. Source: ASHE.



(A) INCOME SHARES OF QUINTILES (B) SELECTED INCOME SHARES

FIGURE C.8. Changes in Income Shares (Relative to 1975). Notes: Raw log earnings and CS sample. Male and Female combined. Shaded areas are recessions. Source: ASHE.

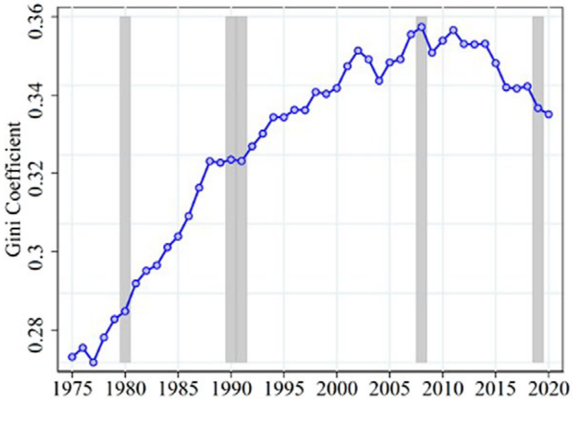
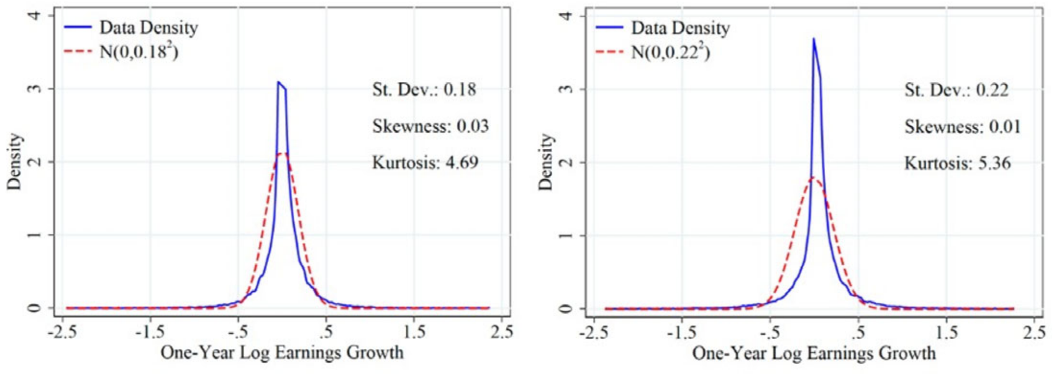
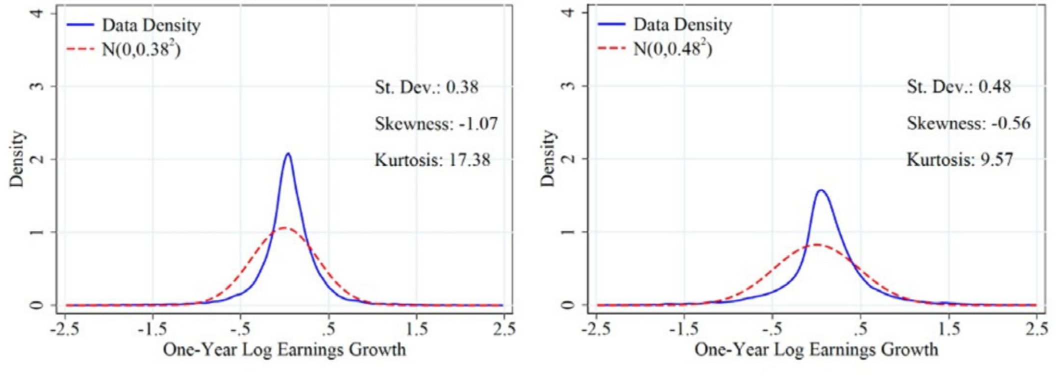


FIGURE C.9. Gini Coefficient. Notes: Gini coefficient constructed using raw log earnings and CS sample. Male and Female combined. Shaded areas are recessions. Source: ASHE.



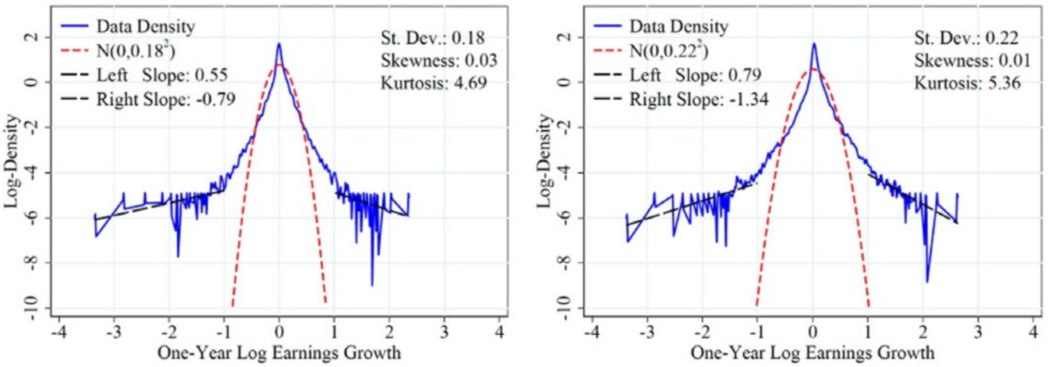
(A) MALE (B) FEMALE

FIGURE C.10. Empirical Densities of 1-year Earnings Growth. Notes: One-year changes in raw log earnings and LX sample. Year 2005. Normal distribution plotted for comparison. Source: ASHE.



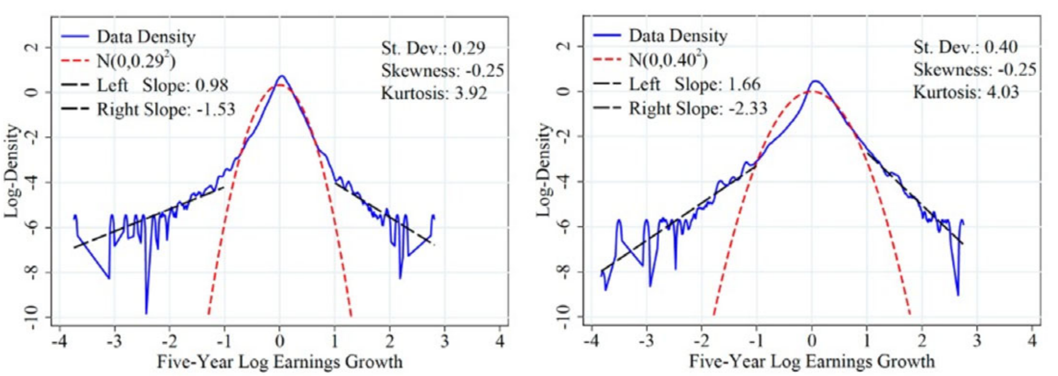
(A) MALE (B) FEMALE

FIGURE C.11. Empirical Densities of 5-year Earnings Growth. Notes: Five-year changes in raw log earnings and LX sample. Year 2005. Normal distribution plotted for comparison. Source: ASHE.



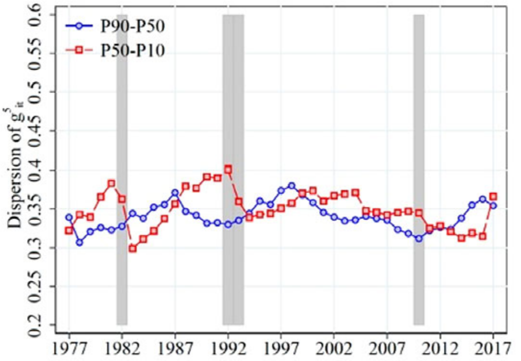
(A) MALE (B) FEMALE

FIGURE C.12. Empirical Log Densities of 1-year Earnings Growth. Notes: One-year changes in raw log earnings and LX sample. Year 2005. Normal distribution plotted for comparison. Source: ASHE.

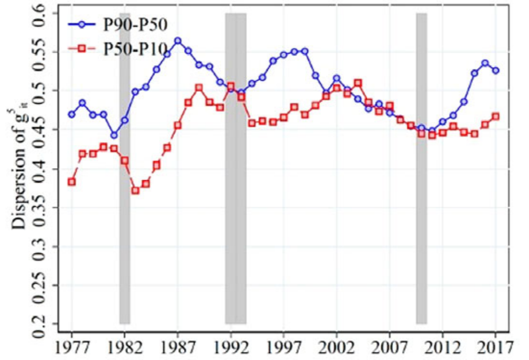


(A) MALE (B) FEMALE

FIGURE C.13. Empirical Log Densities of 5-year Earnings Growth. Notes: Five-year changes in raw log earnings and LX sample. Year 2005. Normal distribution plotted for comparison. Source: ASHE.

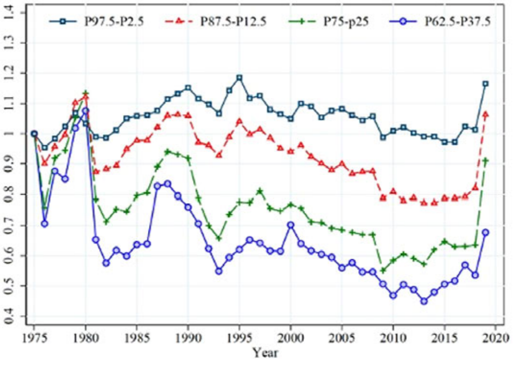


(A) MALE

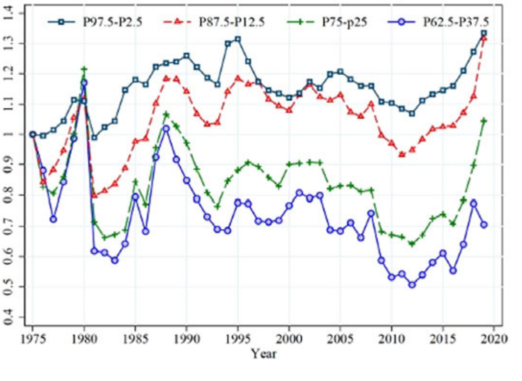


(B) FEMALE

FIGURE C.14. Dispersion of 5-year Log Earnings Changes. Notes: Residual 5-year log earnings changes and LX sample. Shared areas are recessions. Source: ASHE.

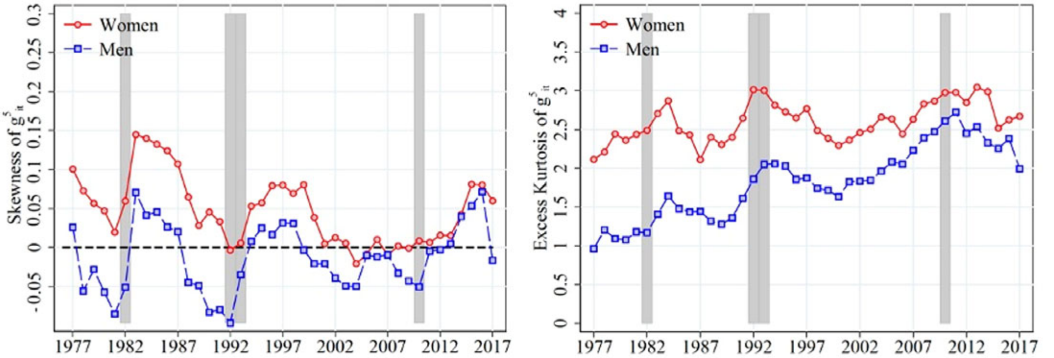


(A) MALE



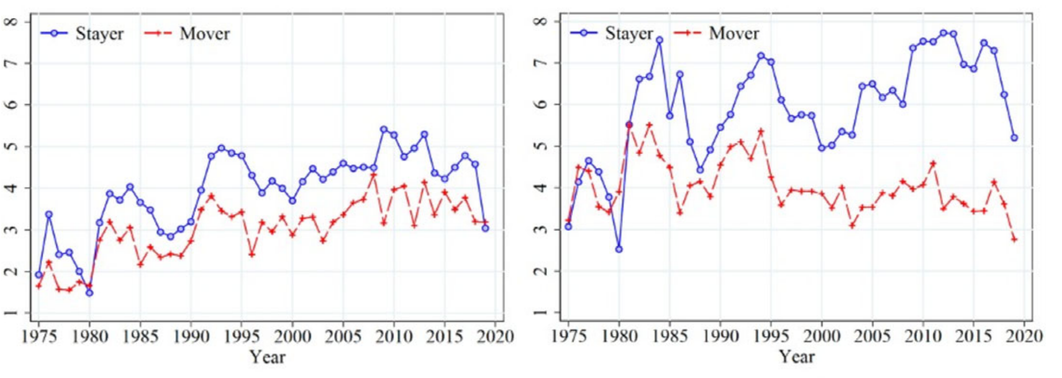
(B) FEMALE

FIGURE C.15. Distribution of Earnings Changes. Notes: Residual 1-year log earnings changes and LX sample. Shared areas are recessions. Each series normalized to 1 in 1975. Source: ASHE.



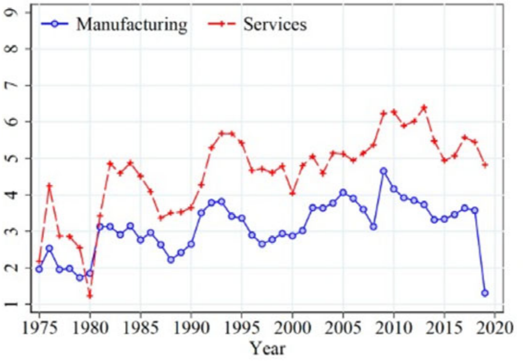
(A) SKEWNESS (B) KURTOSIS

FIGURE C.16. Skewness & Kurtosis of 5-year Log Earnings Changes. Notes: Residual 5-year earnings changes and LX sample. Shaded areas are recessions. Metrics as defined in Figure 6 of main text. Source: ASHE.



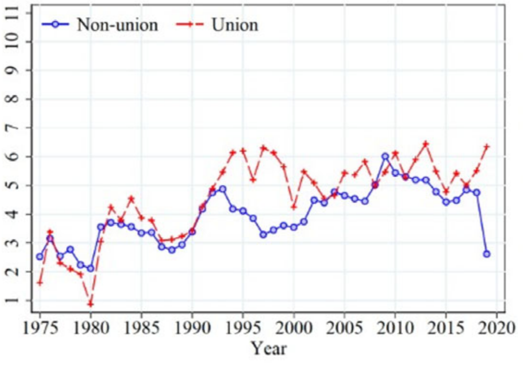
(A) MALE (B) FEMALE

FIGURE C.17. One-Year Kurtosis by Mover/Stayer. Notes: Residual 1-year log earnings changes and LX sample. Shared areas are recessions. Metrics as defined in Figure 6 of main text. Movers defined as those who move firm between t and $t + 1$. Source: ASHE.



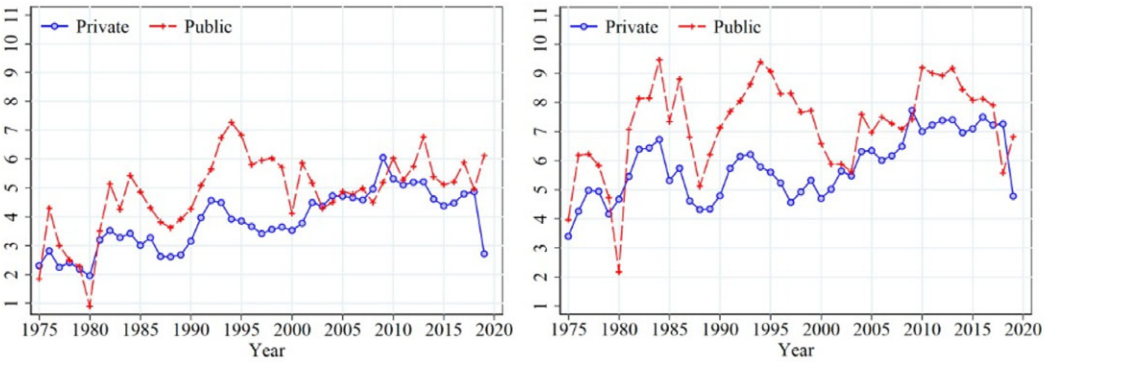
(A) MALE (B) FEMALE

FIGURE C.18. One-Year Kurtosis by Sector. Notes: Residual 1-year log earnings changes and LX sample. Shared areas are recessions. Metrics as defined in Figure 6 of main text. Source: ASHE.



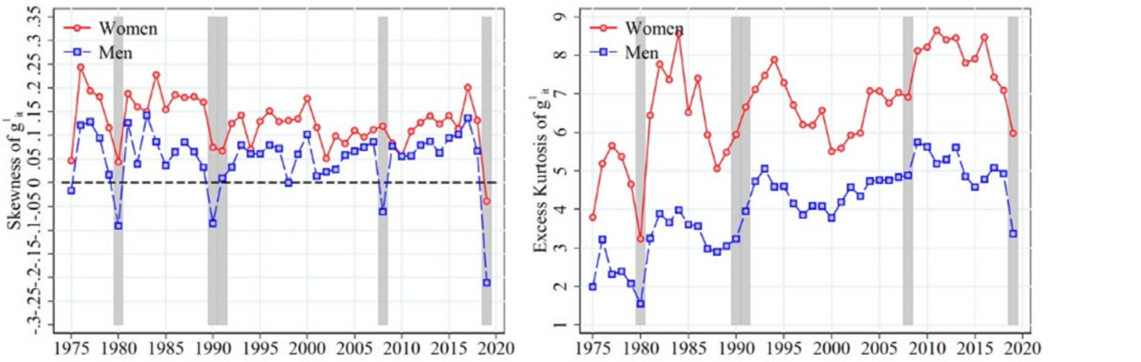
(A) MALE (B) FEMALE

FIGURE C.19. One-Year Kurtosis by Union Status. Notes: Residual 1-year log earnings changes and LX sample. Shared areas are recessions. Metrics as defined in Figure 6 of main text. Source: ASHE.



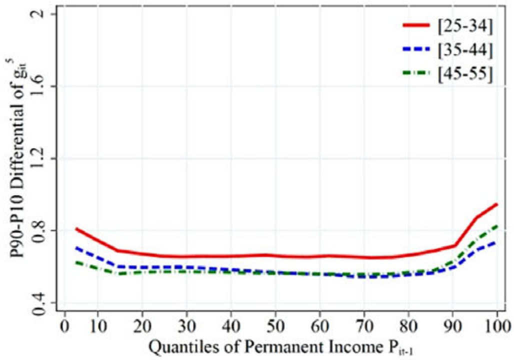
(A) MALE (B) FEMALE

FIGURE C.20. One-Year Kurtosis by Public/Private Sector. Notes: Residual 1-year log earnings changes and LX sample. Shared areas are recessions. Metrics as defined in Figure 6 of main text. Source: ASHE.

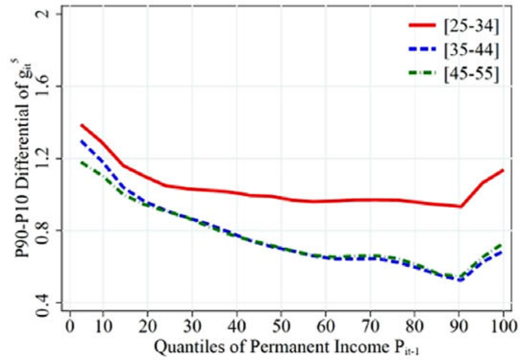


(A) SKEWNESS (B) KURTOSIS

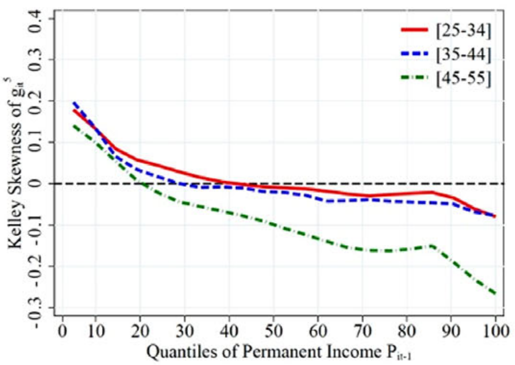
FIGURE C.21. Skewness & Kurtosis of 1-Year Log Earnings Changes (No Lower Threshold). Notes: Residual 1-year earnings changes (including earnings below lower threshold) and LX sample. Shaded areas are recessions. Metrics as defined in Figure 6 of main text. Source: ASHE.



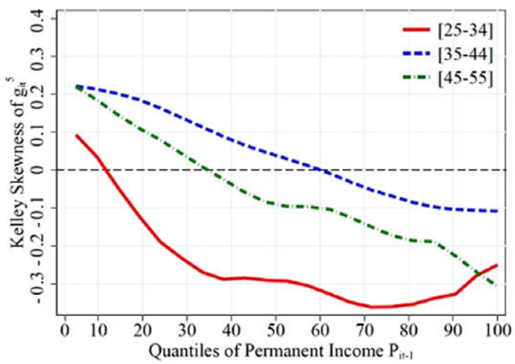
(A) MALE



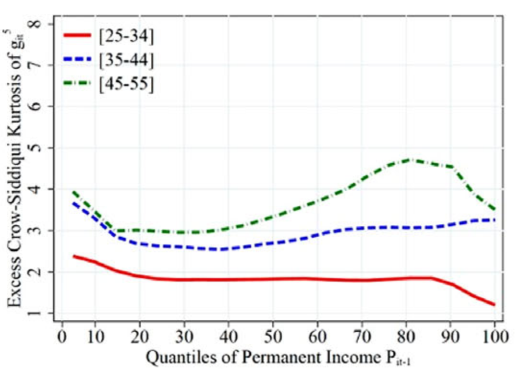
(B) FEMALE



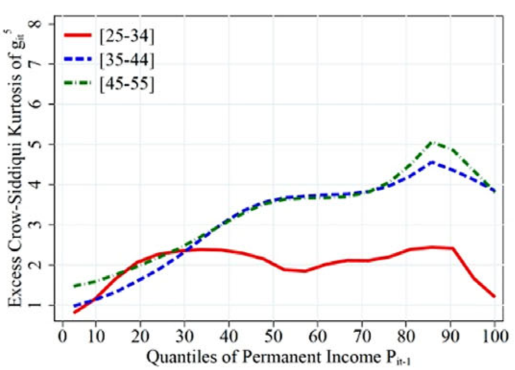
(C) MALE



(D) FEMALE

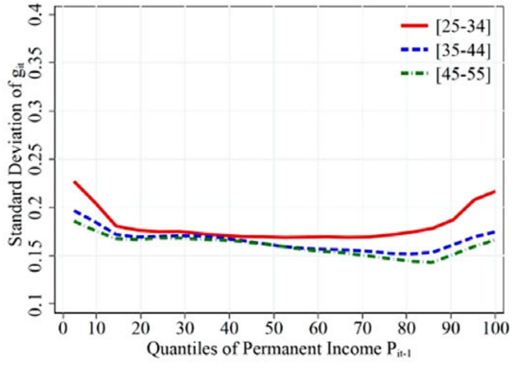


(E) MALE

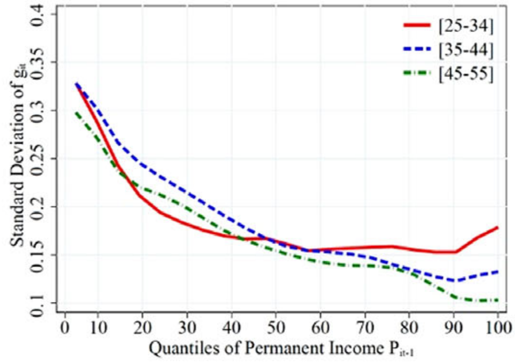


(F) FEMALE

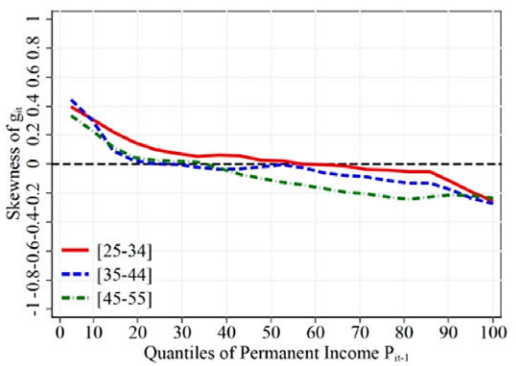
FIGURE C.22. Dispersion, Skewness, and Kurtosis of 5-Year Log Earnings Changes. Notes: Residual 5-year earnings changes and the H sample. Metrics as defined in Figure 7 of main text. Source: ASHE.



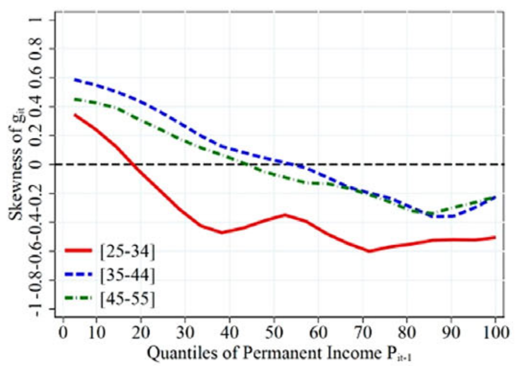
(A) Male



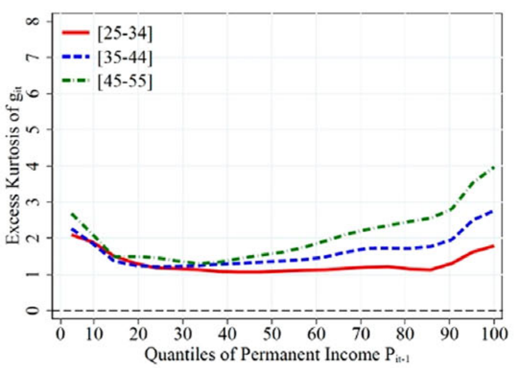
(B) Female



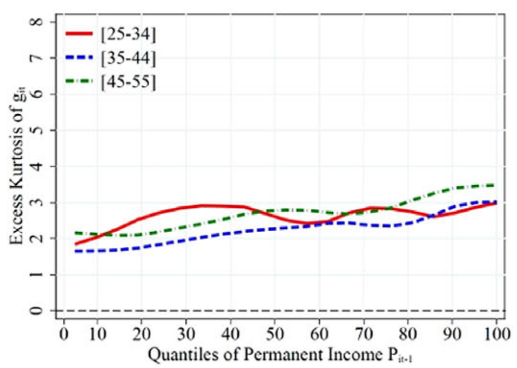
(C) Male



(D) Female

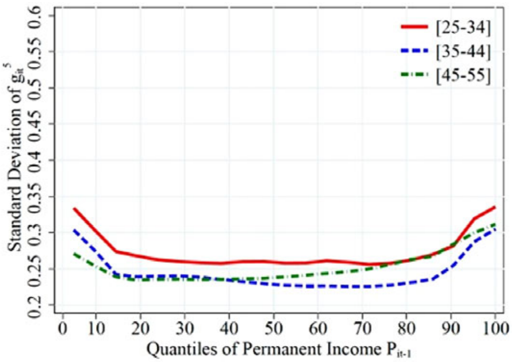


(E) Male

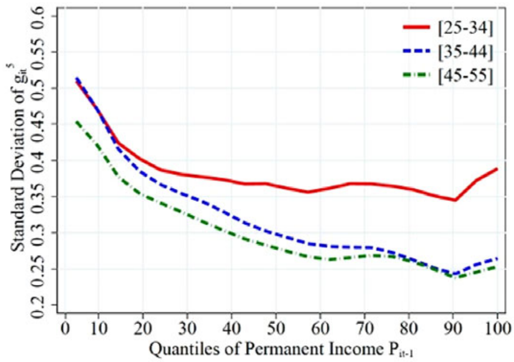


(F) Female

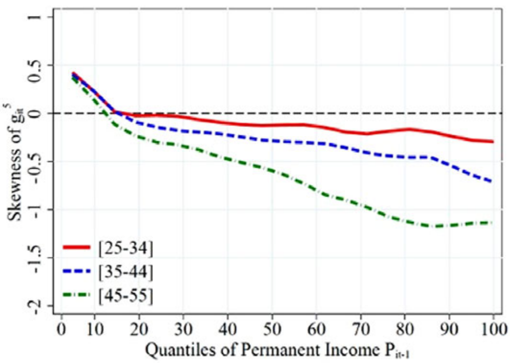
Figure C.23. Standardized Moments of 1-Year Earnings Changes. Notes: Residual 1-year earnings changes and the H sample. Metrics as defined in Figure 7 of the main text. Source: ASHE.



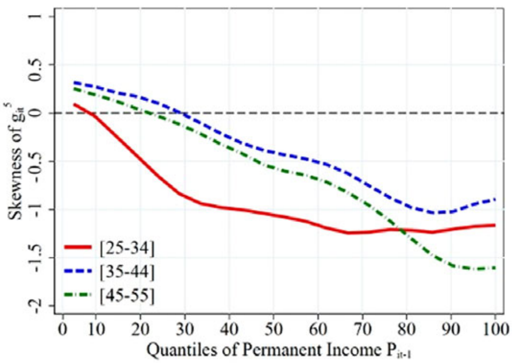
(A) MALE



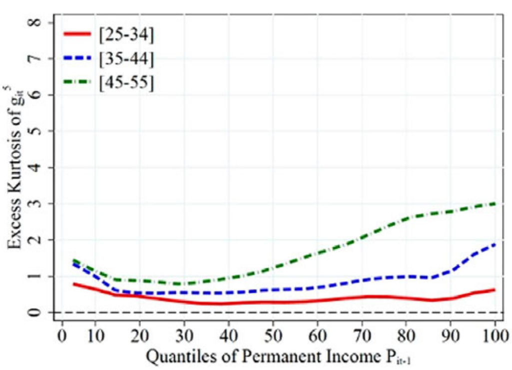
(B) FEMALE



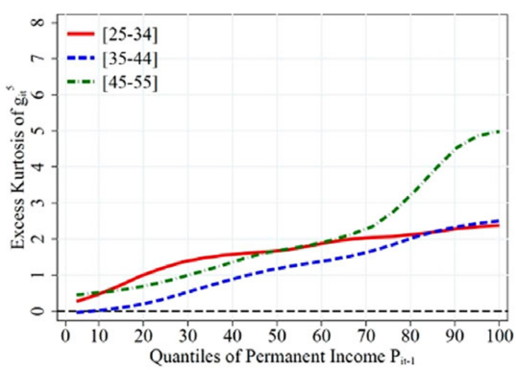
(C) MALE



(D) FEMALE

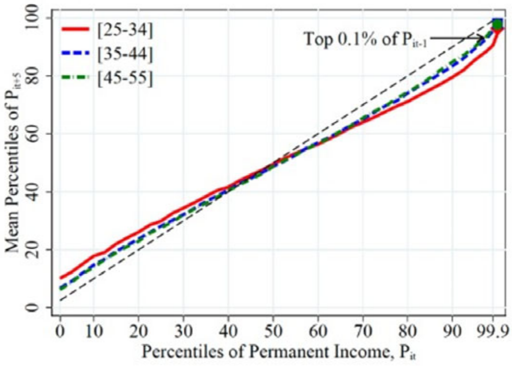


(E) MALE

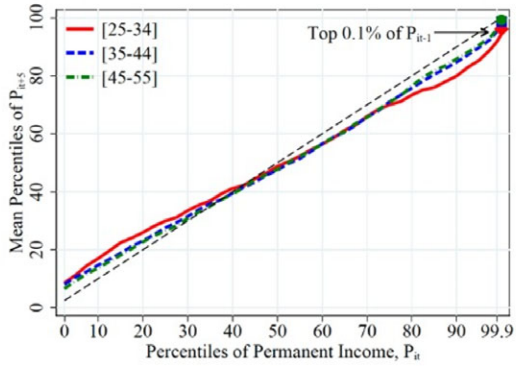


(F) FEMALE

FIGURE C.24. Standardized Moments of 5-Year Earnings Changes. Notes: Residual 5-year earnings changes and the H sample. Metrics as defined in Figure 7 of the main text. Source: ASHE.

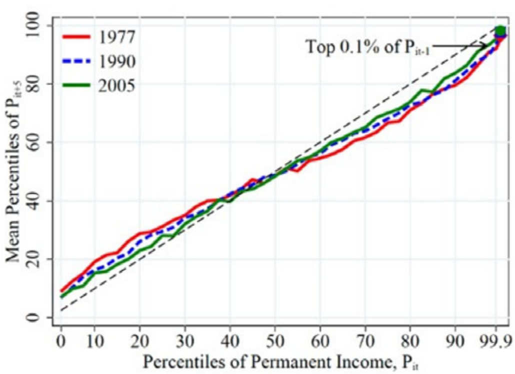


(A) MALE

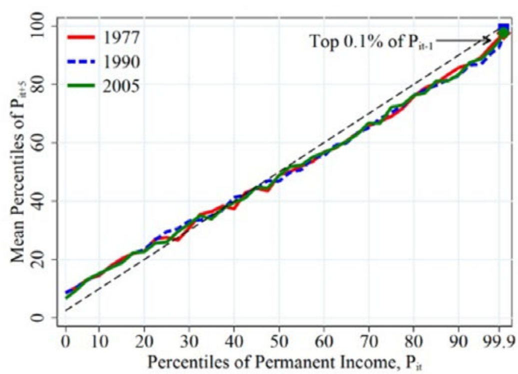


(B) FEMALE

FIGURE C.25. Evolution of 5-year Mobility over the Life Cycle. Notes: Permanent income and sample containing all those with permanent income at t and $t+5$. Metrics as defined in Figure 8 of the main text. Source: ASHE.

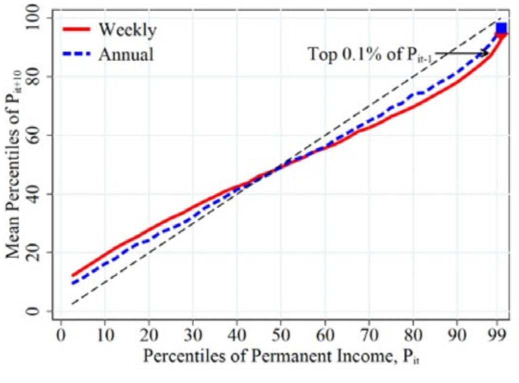


(A) MALE

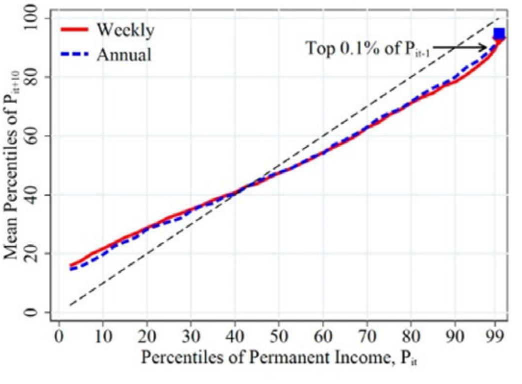


(B) FEMALE

FIGURE C.26. Evolution of 5-year Mobility over Time. Notes: Permanent income and sample containing all those with permanent income at t and $t+5$. Metrics as defined in Figure 9 of the main text. Source: ASHE.



(A) MALE



(B) FEMALE

FIGURE C.27. Comparison of Weekly and Annual 10-year Earnings Mobility. Notes: Permanent income (annual and weekly) and sample containing all those with permanent income at t and $t + 10$. Metrics as defined in Figure 8 of the main text. Restricted to those in the same job as the previous year, years 1998–2020. Source: ASHE.

Appendix D: Additional material for Section 4

Table D.1. Log earnings GDP beta heterogeneity—dynamic specification.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔGDP	0.827	0.964	0.947	1.290	2.843	0.828
	(0.01)	(0.03)	(0.01)	(0.02)	(0.09)	(0.02)
ΔGDP × Female	−0.092					
	(0.01)					
ΔGDP × 25–34		−0.145				
		(0.03)				
ΔGDP × 35–44		−0.192				
		(0.03)				
ΔGDP × 45–54		−0.318				
		(0.03)				
ΔGDP × 55–64		−0.241				
		(0.03)				
ΔGDP × Public			−0.156			
			(0.02)			
ΔGDP × Union			−0.311			
			(0.02)			
ΔGDP × 100–499				−0.275		
				(0.04)		
ΔGDP × 500–1999				−0.427		
				(0.04)		
ΔGDP × 2000+				−0.475		
				(0.03)		
ΔGDP × Mid-Skill					−1.100	
					(0.14)	
ΔGDP × High-Skill					−1.983	
					(0.13)	
ΔGDP × Q2 Earnings						−0.030
						(0.03)
ΔGDP × Q3 Earnings						−0.043
						(0.03)
ΔGDP × Q4 Earnings						−0.087
						(0.03)
ΔGDP × Q5 Earnings						−0.151
						(0.03)
R-Squared	0.002	0.021	0.003	0.003	0.004	0.004
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). Sample is lower in columns (4)–(6) due to missing variables. Standard errors clustered by worker. Years 1975–2020. Estimated coefficients are the sum of the coefficients on the contemporaneous and two lags of ΔGDP. Source: ASHE.

TABLE D.2. Log earnings GDP beta heterogeneity—UKHLS.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔGDP	0.528	0.610	0.385	0.638	0.676	0.925	0.553
	(0.051)	(0.071)	(0.221)	(0.078)	(0.103)	(0.263)	(0.150)
ΔGDP × Female		−0.156					
		(0.102)					
ΔGDP × 25–34			0.115				
			(0.248)				
ΔGDP × 35–44			0.095				
			(0.238)				
ΔGDP × 45–54			0.020				
			(0.239)				
ΔGDP × 55–64			−0.043				
			(0.255)				
ΔGDP × Public				−0.012			
				(0.115)			
ΔGDP × Union				−0.258			
				(0.115)			
ΔGDP × 25–99					−0.231		
					(0.143)		
ΔGDP × 100–999					−0.079		
					(0.132)		
ΔGDP × 1000+					−0.435		
					(0.167)		
ΔGDP × Mid-Skill						−0.304	
						(0.347)	
ΔGDP × High-Skill						−0.228	
						(0.305)	
ΔGDP × Q2 Earnings							−0.221
							(0.196)
ΔGDP × Q3 Earnings							−0.069
							(0.189)
ΔGDP × Q4 Earnings							−0.267
							(0.178)
ΔGDP × Q5 Earnings							−0.082
							(0.181)
R-Squared	0.001	0.001	0.011	0.001	0.001	0.001	0.002
N	156,215	156,215	156,215	154,088	154,876	89,761	122,830

Note: Dependent variable is change in real log monthly earnings. Standard errors clustered by worker. Years 1992–2018, except column (6), which is 2011–2018 to match Table 3 given data constraints on occupation-skill matching. Source: UKHLS.

D.1 *Analysis of the furlough scheme*

On aggregate, 26% of workers are furloughed in our data in April 2020. This aligns well with the ONS statistic of 27% for the same period across the UK workforce, derived from other sources.[8] The scheme was open to all employers, and enabled employers to furlough employees in exchange for a cash grant of 80% of wages, up to GBP 2500 per month. The equivalent annual salary of 2500 per month is close to the median annual salary in the UK in 2020. The employer can choose whether or not to top-up the remaining 20% of pay. While this changed later in the crisis, in April 2020 workers were not able to work any hours for their employer if they had been furloughed.

First, we investigate the characteristics of workers who were likely to be furloughed. In Table D.3 columns (1) and (2), we show estimates from a linear probability model in which the outcome variable is a binary indicator for whether a worker has been furloughed. In column (1), we can see that furlough is more likely for women, younger workers, private sector, and nonunionized workers, those in smaller firms, low-skill workers, and those with shorter firm tenures. These patterns are consistent with the survey evidence presented in Adams-Prassl, Boneva, Golin, and Rauh (2020).

Other than gender, we can see that the patterns here match those shown in the previous subsection. Those whose earnings tend to be more responsive to aggregate shocks are precisely those who were furloughed in the Covid-19 crisis. In column (2), we investigate how the probability of furlough varies by quintiles of permanent income, where permanent income is as defined above. We see a strong profile, with those at the bottom of the permanent income distribution significantly more likely to be furloughed.

Our data also indicates whether employers have opted to top-up furloughed workers' salaries to normal levels. This was asked directly and has not been inferred from earnings data. In Table D.3 columns (3) and (4), we repeat the specifications of columns (1) and (2) with an outcome variable, which equals one if the worker's wages are topped-up by their employer.[9] These regressions include only furloughed workers. On aggregate, approximately half of furloughed workers had their wages topped-up by their employer. In column (3), we can see that middle-aged furloughed workers are the most likely to have their pay topped-up. The coefficient on public sector workers is 0.252, around half the mean value. Furloughed public sector workers are significantly more likely to have their pay topped-up than furloughed private sector workers. However, this is not due to their union coverage. Unionized workers were less likely to have their pay topped-up. There is a U-shaped profile in firm size, with the smallest and largest firms the most likely to top-up furloughed workers wages. Higher skilled workers with more tenure were more likely to have wages topped-up.

In column (4), we again include quintiles of permanent income, showing that workers with higher incomes were more likely to have their wages topped-up. Given the cap at GBP 2500 per month, had these furloughed workers not had their salaries topped-up, they would have seen far more dramatic declines in incomes than lower earning furloughed workers.

How is furlough associated with earnings changes? Table D.4 contains coefficient estimates from a set of regressions where the outcome variable is the change in log earnings between 2019 and 2020. Unsurprisingly, in column (1) we see that being furloughed

[8] ONS "Furloughing of workers across UK businesses: 23 March 2020 to 5 April 2020," released April 23, 2020.

[9] This refers to workers who despite being furloughed, saw no change from their normal rates of pay. Workers whose pay is partially but not fully topped-up will not be included.

TABLE D.3. Furlough and pay top-ups.

	Furlough		Pay top-up	
	(1)	(2)	(3)	(4)
Female	0.018	0.020	0.001	0.005
	(0.00)	(0.00)	(0.01)	(0.01)
Age 25–34	−0.046	−0.073	0.009	0.073
	(0.00)	(0.01)	(0.01)	(0.02)
Age 35–44	−0.061	−0.094	0.046	0.106
	(0.00)	(0.01)	(0.01)	(0.02)
Age 45–54	−0.074	−0.103	0.036	0.098
	(0.01)	(0.01)	(0.01)	(0.02)
55–64	−0.057	−0.082	0.029	0.089
	(0.01)	(0.01)	(0.01)	(0.02)
Public	−0.081	−0.081	0.252	0.222
	(0.00)	(0.01)	(0.03)	(0.03)
Union	−0.034	−0.028	−0.068	−0.061
	(0.00)	(0.00)	(0.02)	(0.02)
Firm Size:				
100–499	−0.121	−0.117	−0.079	−0.075
	(0.00)	(0.00)	(0.01)	(0.01)
500–1999	−0.144	−0.134	−0.042	−0.013
	(0.00)	(0.00)	(0.01)	(0.01)
2000+	−0.195	−0.174	0.087	0.083
	(0.00)	(0.00)	(0.01)	(0.01)
Skill:				
Mid-Skill	−0.020	−0.000	0.041	0.035
	(0.00)	(0.00)	(0.01)	(0.01)
High-Skill	−0.092	−0.038	0.111	0.073
	(0.00)	(0.00)	(0.01)	(0.01)
Tenure 1–2 yrs	0.005	−0.006	0.009	0.003
	(0.00)	(0.01)	(0.01)	(0.01)
Tenure 3–4 yrs	−0.003	0.001	0.030	0.035
	(0.00)	(0.01)	(0.01)	(0.01)
Tenure 5–9 yrs	−0.020	−0.016	0.025	0.021
	(0.00)	(0.01)	(0.01)	(0.01)
Tenure 10+ yrs	−0.026	−0.019	0.024	0.018
	(0.00)	(0.01)	(0.01)	(0.01)
Earnings Q2		−0.011		−0.030
		(0.00)		(0.01)
Earnings Q3		−0.041		0.008
		(0.00)		(0.01)
Earnings Q4		−0.070		0.029
		(0.00)		(0.01)

(*Continues*)

TABLE D.3. *Continued.*

	Furlough		Pay top-up	
	(1)	(2)	(3)	(4)
Earnings Q5		−0.110		0.063
		(0.00)		(0.02)
Constant	0.317	0.346	0.391	0.287
	(0.01)	(0.02)	(0.04)	(0.06)
Dep Mean	0.254	0.254	0.524	0.524
R-Squared	0.304	0.294	0.070	0.080
N	110,346	74,985	28,044	17,044

Note: Linear probability model with outcome variable = 1 if worker is furloughed in columns (1)–(2) and outcome variable = 1 if pay topped-up by employer in columns (3)–(4). Year 2020. Source: ASHE.

TABLE D.4. Earnings changes and furlough across the earnings distribution.

	(1)	(2)	(3)	(4)
Furloughed	−0.150		−0.154	
	(0.00)		(0.01)	
Furloughed (No top-up)		−0.237		−0.223
		(0.00)		(0.01)
Furloughed (Top-up)		−0.087		−0.086
		(0.00)		(0.00)
Earnings (interactions):				
Q2 × Furloughed			0.004	
			(0.01)	
Q3 × Furloughed			0.007	
			(0.01)	
Q4 × Furloughed			0.010	
			(0.01)	
Q5 × Furloughed			−0.007	
			(0.01)	
Q2 × Furloughed (No top-up)				−0.018
				(0.01)
Q3 × Furloughed (No top-up)				0.003
				(0.01)
Q4 × Furloughed (No top-up)				−0.022
				(0.01)
Q5 × Furloughed (No top-up)				−0.079
				(0.01)
Dep var mean	0.006	0.006	0.006	0.006
R-squared	0.088	0.108	0.088	0.108
N	56,788	56,788	56,788	56,788

Note: Outcome variable is change in log earnings from 2019 to 2020. All specifications include controls for age, sex, skill level, firm size, public sector, union coverage, plus two-digit industry fixed effects. Years 2019–2020. Source: ASHE.

TABLE D.5. Log earnings firm-shock heterogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)
log(VAPW)	0.061	0.036	0.062	0.055	0.024	0.054
	(0.013)	(0.013)	(0.013)	(0.013)	(0.018)	(0.013)
log(VAPW) × Female	−0.076					
	(0.028)					
log(VAPW) × 25–34		0.033				
		(0.002)				
log(VAPW) × 35–44		0.036				
		(0.002)				
log(VAPW) × 45–54		0.033				
		(0.002)				
log(VAPW) × 55–64		0.019				
		(0.003)				
log(VAPW) × Union			−0.001			
			(0.001)			
log(VAPW) × 100–499				0.002		
				(0.002)		
log(VAPW) × 500–1999				0.006		
				(0.002)		
log(VAPW) × 2000+				0.010		
				(0.003)		
log(VAPW) × Mid-Skill					0.021	
					(0.003)	
log(VAPW) × High-Skill					0.027	
					(0.003)	
log(VAPW) × Q2 Earnings						0.002
						(0.001)
log(VAPW) × Q3 Earnings						0.006
						(0.002)
log(VAPW) × Q4 Earnings						0.012
						(0.002)
log(VAPW) × Q5 Earnings						0.023
						(0.002)
N	325,472	325,472	325,472	325,470	137,028	233,584

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) from matched FAME data (column (2) of Table 5). Source: ASHE/ARD/FAME.

is associated with a 15-log point drop in earnings. While we include a wide set of controls including two-digit industry fixed effects, we do not claim this to be causal, as there will be strong selection into which types of workers are chosen for furlough. In column (2), furlough is split into those whose employer tops-up their salary and those whose do not. Even among workers whose salary is topped-up, there is a greater fall in earnings than nonfurloughed workers. This could be selection (on earnings trajectory) or could

Table D.6. Log earnings firm-shock heterogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)
log(VAPW)	0.028	0.001	0.029	0.024	−0.005	0.019
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.011)
log(VAPW) × Female	0.052					
	(0.022)					
log(VAPW) × 25–34		0.033				
		(0.002)				
log(VAPW) × 35–44		0.038				
		(0.002)				
log(VAPW) × 45–54		0.035				
		(0.002)				
log(VAPW) × 55–64		0.023				
		(0.002)				
log(VAPW) × Union			−0.001			
			(0.001)			
log(VAPW) × 100–499				−0.001		
				(0.002)		
log(VAPW) × 500–1999				0.003		
				(0.002)		
log(VAPW) × 2000+				0.006		
				(0.003)		
log(VAPW) × Mid-Skill					0.021	
					(0.002)	
log(VAPW) × High-Skill					0.028	
					(0.002)	
log(VAPW) × Q2 Earnings						0.001
						(0.001)
log(VAPW) × Q3 Earnings						0.004
						(0.001)
log(VAPW) × Q4 Earnings						0.011
						(0.002)
log(VAPW) × Q5 Earnings						0.023
						(0.002)
N	479,185	479,185	479,185	479,182	190,994	345,798

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 lagged value of log(VAPW) (column (3) of Table 5). Source: ASHE/ARD.

be due to employers' misinterpreting the question. In column (3), we interact furlough with permanent earnings. All interactions are estimated precisely and are insignificantly different to zero. The zero coefficients here are interesting, as they suggest that the earnings drop associated with being furloughed does not differ across workers of different permanent incomes.

TABLE D.7. Log earnings firm-shock heterogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)
log(VAPW)	0.062	0.036	0.061	0.059	0.015	0.055
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)
log(VAPW) × Female	−0.080					
	(0.034)					
log(VAPW) × 25–34		0.032				
		(0.002)				
log(VAPW) × 35–44		0.035				
		(0.003)				
log(VAPW) × 45–54		0.031				
		(0.003)				
log(VAPW) × 55–64		0.019				
		(0.003)				
log(VAPW) × Union			−0.001			
			(0.001)			
log(VAPW) × 100–499				0.000		
				(0.002)		
log(VAPW) × 500–1999				0.005		
				(0.003)		
log(VAPW) × 2000+				0.007		
				(0.003)		
log(VAPW) × Mid-Skill					0.022	
					(0.003)	
log(VAPW) × High-Skill					0.027	
					(0.003)	
log(VAPW) × Q2 Earnings						0.000
						(0.001)
log(VAPW) × Q3 Earnings						0.003
						(0.002)
log(VAPW) × Q4 Earnings						0.008
						(0.002)
log(VAPW) × Q5 Earnings						0.018
						(0.003)
N	281,996	281,996	281,996	281,994	132,331	203,821

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 all three potential instruments (column (4) of Table 5). Source: ASHE/ARD/FAME.

This is capturing two offsetting effects. While furloughed workers of higher incomes are more likely to have their salaries topped-up by employers, among the minority whose employers do not top-up their salaries, the income loss is substantial as they are paid the maximum furlough level of GBP 2500 per month. This is shown through the interactions in column (4). Workers of higher permanent incomes who do not have their salaries topped-up see a far greater fall in earnings from 2019–2020.

The furlough scheme is the first of its kind in the UK. While it is challenging to assess the causal impact of the introduction of the furlough scheme on earnings inequality and volatility, we can see clearly here that those who are furloughed receive a substantial earnings shock on average, and that those who were already low earners are most likely to be furloughed. However, given the economic context, it has undoubtably dampened the employment effects of the Covid-19 shock. Taking these results together, in terms of labor market earnings, having access to the furlough scheme has likely increased inequality and earnings volatility in 2020. In a counterfactual without furlough, these workers would likely have been laid off and reliant on savings and other social safety nets, so the effect of furlough on total income (including non-labor income) is likely to be very different.

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