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Abstract

This paper examines the relationship between idiosyncratic risk in labour income and fluctuations in aggregate labour market quantities for Great Britain. We use data from the British Household Panel Survey (BHPS) for 1991-2008 and from the BHPS sub-sample of Understanding Society for 2010-2014. We measure idiosyncratic risk in labour income by the relevant moments of the distributions of earnings, employment and wage shocks across individuals. Our main finding is that idiosyncratic risk increases during contractions in the labour market. Furthermore, we find evidence of insurance, both at the household level and in the form of public insurance. However, private and public insurance mechanisms against an increase in idiosyncratic risk are less e¤ective for households whose head does not hold a University degree.

JEL-Codes: D310, E240, J310.

Keywords: idiosyncratic income risk, employment, social insurance policy.

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1 Introduction

This paper examines the relationship between idiosyncratic risk in labour income and fluctuations in aggregate labour market quantities for Great Britain from 1991–2014. Idiosyncratic risk in labour income refers to earnings, employment and wage risk. Understanding labour income risk has important implications for both economic theory and economic policy (see e.g. Guvenen *et al.* (2014), Meghir and Pistaferri (2011) and Low *et al.* (2010)). In response to increased labour income risk, individuals engage in a number of *ex ante* precautionary and *ex post* corrective economic activities, which ultimately can affect aggregate economic outcomes (see e.g. Meghir and Pistaferri (2011) for a review of the literature). For example, precautionary behaviour related to higher labour income risk may lead to increases in savings and labour supply as well as portfolio adjustments to include more lower-risk lower-return assets. These responses are of course stronger under incomplete markets. In contrast, *ex post* responses to negative shocks to labour income might include the liquidation of assets and durable goods, changing jobs as well as family labour supply. The absence of market opportunities for insurance against negative shocks to labour income typically motivates public insurance.[1]

The relationship between idiosyncratic risk and aggregate fluctuations is also important in understanding macroeconomic phenomena. In particular, theoretical work has focused on the role of countercyclical risk in explaining asset prices and economic fluctuations (see e.g. Storesletten *et al.* (2004) and Guvenen *et al.* (2014) for a summary and references). The main idea is that idiosyncratic labour income risk is increasing with respect to negative aggregate shocks. In this literature, some studies have concentrated on the importance of the countercyclical variance of earnings shocks (e.g. Constantinides and Duffie (1996) and Storesletten *et al.* (2007) while others have highlighted the significance of the countercyclical left-skewness of earnings shocks (e.g. Mankiw (1986), Brav *et al.* (2002), Krebs (2007) and Constantinides and Ghosh (2014)).

This theoretical work has motivated empirical research which examines the relationship between second and higher moments of the distribution of individual labour income shocks and aggregate fluctuations. For example, Storesletten *et al.* (2004) focused on the cyclical properties of the variance of earnings shocks by estimating a model for earnings dynamics with a regime-

[1] Such negative shocks can take the form of unemployment or health shocks that reduce employment, or shocks that reduce returns to work, e.g. shocks that lower productivity, technology shocks that make skills less valuable and shocks leading to employer-worker mismatch.

switching variance using U.S. panel (PSID) data and find that the variance for household labour income (earnings plus benefits) is countercyclical. Guvenen *et al.* (2014) use U.S. Social Security Administration data, and without imposing restrictions on the shape of the distribution of shocks to individual earnings, find that the left-skewness is countercyclical and not the variance. These results have been extended using panel data surveys for Germany, Sweden and the U.S. in Busch *et al.* (2016), who also find evidence of countercyclical left-skewness for wages (for Germany) and household-level income measures. Moreover, Busch and Ludwig (2016), using data for Germany for individuals and households, extend the approach in Storesletten *et al.* (2004) and estimate a model for earnings dynamics that allows for regime-switching variance and skewness. They find that both the variance and left-skewness fall in periods of aggregate expansion and improved labour market conditions.

The general message from these studies is that, for these countries at least, labour income risk is asymmetric, being higher (lower) when aggregate outcomes deteriorate (improve).[2] In addition to the usefulness of these results for theoretical analysis, these findings suggest that more public insurance may be required when negative aggregate shocks hit the economy. In most of these studies (although see e.g. Busch and Ludwig (2016) for an exception), fluctuations in aggregate conditions are captured by changes in GDP since these tend to correlate well with labour market magnitudes relevant for idiosyncratic earnings risk. Depending on the country and time period under study however, this might not be a good assumption.[3]

For instance, in the U.K., in the period 1991–2014 for which we have panel data, there are only two periods with a negative GDP growth rate.[4] However, despite positive GDP growth rates for most of the period, aggregate (average) earnings, employment and wages demonstrate patterns with significant fluctuations and a number of periods of negative growth.[5] This implies the presence of different factors that contribute to a contraction/expansion

[2]For Great Britain, Bayer and Juessen (2012) find that the variance of idiosyncratic shocks to wages is acyclical. Similarly, regarding the variance of individual earnings growth, Cappellari and Jenkins (2014) find that it has remained effectively constant over the 1991-2008 period. Blundell and Etheridge (2010) provide an overview of the evolution of inequality at the individual and household level in the UK.

[3]Busch *et al.* (2016) also make the point that periods officially defined as recessions need not capture all the negative aggregate shocks that are relevant for idiosyncratic labour income risk.

[4]These refer to the first period and the recession in 2008-2009. In fact, since BHPS data are available for 1991-2008 and continue, via the Understanding Society database, for 2010-2014, an analysis using growth in earnings to approximate idiosyncratic shocks has only one period of negative GDP growth in the sample.

[5]This is discussed in more detail below, and shown graphically in Figure 1.

of these aggregates which are not necessarily related to fluctuations in GDP in the same period. Such factors may relate to capital-biased technological change, deregulation of labour markets, or certain effects of globalisation, which can lead to a reduction in mean earnings, employment and wages, while also contributing to increases in aggregate output.[6] In light of these considerations for Great Britain, instead of GDP, we use aggregate labour market measures of the cycle based on changes in average: (i) annual earnings; (ii) annual hours of work; and (iii) hourly wages.[7]

To relate idiosyncratic earnings, employment and wage risk to fluctuations in these labour market aggregates in Great Britain, we employ panel data from the British Household Panel Survey (BHPS) for 1991-2008 and from the BHPS sub-sample of Understanding Society for 2010-2014. More specifically, we start by deriving the distribution of shocks to earnings across individuals by calculating the growth rate of residual earnings for each individual between consecutive periods.[8] To obtain residual earnings, we partial out changes in earnings that are due to observables, in the form of experience, gender, region and education, to focus on genuine idiosyncratic effects. We do not impose restrictions on the shape of the distribution of idiosyncratic shocks to earnings, motivated by recent research and findings in Guvenen *et al.* (2014) and Busch *et al.* (2016).

We next measure earnings risk by moments that capture the shape of the cross-sectional residual earnings growth distribution. In particular, we calculate the variance, skewness and changes in the tails, specifically the distance between the 90th and 50th and between the 50th to 10th percentiles (which we denote as $P90/50$ and $P50/10$ respectively). We finally relate these moments to changes in aggregate earnings. In particular, we: (i) examine how these moments differ between periods of positive and negative aggregate earnings growth; (ii) relate these moments, via a regression analysis following Busch *et al.* (2016), to continuous changes in aggregate earnings growth.

We then undertake the same analysis for individual wages (hourly wage) and employment (annual hours) as well as for household labour income, gross income and disposable income.[9] We also examine potential heterogeneity

[6] Busch and Ludwig (2016) point out that a potential drawback with using GDP based definitions for recessions is imperfect synchronisation of the labour market.

[7] Section 3 and Appendix A explains the data we use in more detail and how we construct the series for changes in aggregate labour market quantities.

[8] Following Guvenen *et al.* (2014) and Busch *et al.* (2016) we also look at the more general measure of earnings shocks, using the growth rate of earnings for each individual, for robustness and completeness. This measure has also been used for the analysis of earnings and labour market volatility in Great Britain in Cappellari and Jenkins (2014).

[9] For the household quantities, because we are interested in within-household and public insurance against idiosyncratic shocks, we relate the moments of the respective distribu-

in the properties of idiosyncratic earnings, employment and wage risk by applying to the same analysis to males with and without a University degree, and to females.

The rest of the paper is organised as follows. After providing an overview of the main results, we discuss in more detail, in Section 2, the empirical methodology and in Section 3 the data used in the analysis. We then present and analyse the results in Section 4. After providing the conclusions and discussion in Section 5, we include Appendices with further details on the data and additional empirical results.

1.1 Main Findings

Our main finding is that earnings, employment and wage risk are asymmetric with respect to aggregate labour market outcomes in Great Britain, being higher (lower) when aggregate outcomes deteriorate (improve). Our results for earnings risk over the period 1991-2008, are broadly consistent with previous findings in Guvenen *et al.* (2014) and Busch *et al.* (2016) for Germany, Sweden and the U.S. regarding the importance of changes in the tails of the distribution. We find that the left-skewness of the idiosyncratic (residual) earnings growth distribution for males increases but the variance does not change when mean earnings are reduced.[10] Moreover, in such periods, the left-skewness of the distributions of idiosyncratic shocks to earnings and income at the household level also increases. However, insurance mechanisms at the household level and government policy reduce the increase in household income risk, especially for households whose head is University educated. University education matters, both for wage and employment risk, at the individual level, as well as for the effectiveness of private and public insurance mechanisms against an increase in idiosyncratic risk, at the household level.

Starting with individual earnings risk, the results suggest that when aggregate earnings fall, the spread of the distribution of idiosyncratic earnings shocks does not change. This is consistent with previous research for Great Britain in Cappellari and Jenkins (2014), who find that the variance of idiosyncratic earnings growth has remained more or less constant over the 1991-2008 period. However, our results show that left-skewness increases, and in particular that the relative concentration on the lower tail increases, when aggregate earnings fall. In turn, this implies an increase in the probability of

tions to changes in mean male earnings.

[10]The skewness results are similar for females. However, there is also an indication of a positive relationship between the variance and mean earnings growth. This suggests a greater variance in female labour supply in better times. These results are also qualitatively similar to those reported in Busch *et al.* (2016).

big negative idiosyncratic earnings shocks in periods when aggregate earnings contract.

To further explore asymmetry in labour income risk, we examine the risk associated with employment and wages. We find that the Kelly skewness of the relevant idiosyncratic distributions for both employment and wages falls with reductions in mean employment and wages, respectively. These results suggest that periods of negative shocks to labour are associated with a lower probability of high wages and a higher probability of reductions in employment (see e.g. Busch *et al.* (2016) for related evidence for the former for Germany and Blass-Hoffmann and Malacrino (2016) for related evidence on the latter for Italy and the U.S.).

A further difference between wages and employment relates to the spread of the distribution of idiosyncratic shocks. More specifically, while the variance of the distribution of idiosyncratic wages shocks increases with reductions in mean wages, the variance of the distribution of idiosyncratic employment shocks decreases with reductions in mean employment. The comovement of the variance in the distribution of shocks to employment suggests that workers have more options to spread out, in terms of labour supply, in periods of expansion to employment. This implies more opportunities for matching idiosyncratic labour supply with available options for employment. On the other hand, in periods of decreased demand for labour, such flexibility is reduced since demand is more important in determining equilibrium outcomes, so that workers cluster closer to the mean.

We also detect heterogeneity between University and non-University educated individuals regarding wage risk, but not earnings risk. In particular, we find that the increase in relative skewness for wage shocks in periods of lower wage growth applies to the non-University educated, suggesting that wages for University educated are better protected from negative shocks at the aggregate level. Regarding employment, both groups of individuals face an expansion of the lower tail in periods of reduced employment growth. However, while the upper tail contracts for non-University educated workers, it expands for University educated workers.

We finally find evidence of insurance, both at the level of the household and in the form of public insurance. In particular, we first find that households overall reduce the increase in left-skewness of the earnings shocks that their members experience, following shocks to individual earnings. We then find that households reduce the increase in skewness from household earnings shocks to household gross income shocks (private insurance), although this result is driven by the group of households whose head is University educated. In particular, we find that the relevant reduction for households whose head is not University educated is very small. Finally, we find that government policy reduces, but does not eliminate, the increase in skewness in household gross income shocks by using taxes and transfers (public insurance). In particular, while the increase in household net income risk is smaller relative to that estimated for gross income risk, for those households whose head does not have a University degree, the increase in skewness in the distribution of shocks to disposable income remains significant.

2 Empirical Methodology

This section first summarises the methods we use to characterise the distributions of shocks to individual earnings, employment and wages as well as household income. We then discuss the methods used to relate these distributions to changes at the aggregate level.

2.1 Distribution of idiosyncratic shocks

We denote the natural logarithm of each of the components of labour income as $y_{i,t}$. To characterise the distribution of shocks to these measures, we: (i) approximate the shock to $y_{i,t}$ by the changes over time to actual $y_{i,t}$ and to its unobservable component, $\mu_{i,t}$; (ii) construct the distribution of shocks across i for each t; and (iii) obtain the moments or other properties of the distribution that are of interest. Given that data are available for either 18 or 23 years (see Section 3 and Appendix A for details), we look at annual changes in $y_{i,t}$ or its unobservable component, which implies that such idiosyncratic shocks contain both permanent and transitory effects, a point we return to when discussing our results.

2.1.1 Earnings, employment and wage growth

We first approximate the shock to $y_{i,t}$ by calculating its growth rate as a log-difference, $\Delta y_{i,t} \equiv y_{i,t} - y_{i,t-1}$ (see also e.g. Guvenen *et al.* (2014), Cappellari and Jenkins (2014) and Busch *et al.* (2016)). Then, for each time period t, we construct the distribution of changes or shocks $\Delta y_{i,t}$ across individual units i, and calculate measures of its variance and skewness. Individual units may be the male or female individuals in the sample, or the households, as appropriate. Calculating shocks in this fashion relies on the assumption that individual-specific characteristics that determine each of the components of labour income are constant in the short-run and thus drop out when taking first differences. Such characteristics include e.g. ability, gender, and, to the extent that they and their effect on the earnings measure of interest does not change over the time period, other factors like e.g. education or region of residence.

The advantage of this approach to approximating shocks is that it does not impose any assumption on which part of the income change counts as a "shock".[11] It also allows a qualitative comparison of our results with those in Busch *et al.* (2016), who also use similar longitudinal datasets for the U.S., Germany and Sweden. One disadvantage of this framework is that changes in income need not only reflect genuine uncertainty, but also changes in observables. For example, in years of experience, but also, for certain individuals, education and region of residence may change over the period considered. Moreover, even if the characteristics do not change, their effect on determining the income measure of interest can change (and in fact we find that it does). To partially control for this, we also construct the distribution of shocks $\Delta y_{i,t}$ and calculate the respective descriptive statistics for groups of the sample defined by potentially important differences in characteristics relating to labour income. In particular, we look at the sub-samples of university educated versus non-university educated individuals, while we always consider male and female individuals separately.

2.1.2 Residual earnings, employment and wage growth

To focus more directly on idiosyncratic shocks capturing unpredictable changes, and exploit the information on individual observables available in the BHPS dataset, we also employ a two-step approach to obtain these shocks. Its advantage is that it combines ideas from the research on residual earnings (see e.g. Meghir and Pistaferri (2011) for a review), which allows us to partial out the effect of observables on changes in earnings; and the approach in Guvenen *et al.* (2014) and Busch *et al.* (2016), which does not impose restrictions on the shape of unobservable earning dynamics.

Individuals Suppose that, for example, the log earnings for an individual follows the process:

$$y_{i,t} = f_t(EX_{i,t}) + g_t(x_{i,t}) + \mu_{i,t} \tag{1}$$

where $f_t(EX_{i,t})$ is a deterministic function of age, capturing effects of experience on earnings; the function $g_t(x_{i,t})$ includes other observable characteristics which may affect individual labour income, e.g. family composition, gender, education, race, region of residence; and $\mu_{i,t}$ is the unobserved

[11] Cappellari and Jenkins (2014) also review the literature and discuss the benefits of "simple measures" of earnings volatility.

idiosyncratic component, net of the predictable components, $f_t(EX_{i,t})$ and $g_t(x_{i,t})$. Note that both of these predictable components depend on time, implying that the coefficients capturing the effect of observables are allowed to be time-varying.

Following the literature, (see e.g. Meghir and Pistaferri (2004), Ramos (2003) an Mincer (1974)) we specify a quadratic relationship for the effect of experience, so that:

$$f_t(EX_{i,t}) \equiv \beta_{1,t}EX_{i,t} + \beta_{2,t}EX_{i,t}^2 \tag{2}$$

where $EX_{i,t}$ is the age of the respondent and captures potential labour market experience, implicitly assuming that experience is increasing linearly with the age (see, e.g. Hrysko (2012) and Mincer (1974)). Moreover, $g_t(x_{i,t})$ is defined as:

$$\sum\nolimits_{j=2}^{4} \beta_{j,t}ED_i + \sum\nolimits_{\kappa=5}^{14} \beta_\kappa R_i \tag{3}$$

where ED_i are dummies for educational attainment and R_i are dummies for region. Following Blundell and Etheridge (2010) we use the following education categories: (i) 'high education' includes those with a higher or first degree, city and guilds certificates, and other higher diplomas; (ii) 'intermediate education' includes those with A-levels or equivalent; (iii) and 'low education' is the remainder. For region dummies we use the UK Government Office Regions classification which corresponds with the highest tier of sub-national division in England, plus Scotland and Wales.

Therefore, we have the following regression:

$$y_{i,t} = \beta_{0,t} + \beta_{1,t}EX_{i,t} + \beta_{2,t}EX_{i,t}^2 + \sum\nolimits_{j=3}^{4} \beta_{j,t}ED_i + \sum\nolimits_{\kappa=5}^{14} \beta_\kappa R_i + \mu_{i,t} \tag{4}$$

where β_0 is interpreted as a male residing in the North East region without experience and low education.

We run least squares regressions using equation (4) for each year separately, since we find that the effect of the observables changes over time, and in each year we keep the residuals $\widehat{\mu}_{i,t}$ which provide a proxy for the unobserved component of $y_{i,t}$. By differencing $\widehat{\mu}_{i,t}$ we obtain a measure of the change in the idiosyncratic component, $\Delta\widehat{\mu}_{i,t} \equiv \widehat{\mu}_{i,t} - \widehat{\mu}_{i,t-1}$ which, we use as a measure of the idiosyncratic earnings shock. Note that we have not imposed restrictions on the shape of the distribution of $\mu_{i,t}$, so that while we have decomposed earnings to a predictable and an unpredictable component by using parametric restrictions, the obtained distribution of the unpredictable component (and thus of its changes) is not restricted. In turn, this implies that idiosyncratic earnings shocks may have a distribution where higher moments can change over time. Finally, we use the distribution of residual growth rates across individuals to calculate descriptive statistics of interest.

Households To decompose household income quantities and calculate moments of the shocks to the unpredictable component we work as above by letting $y_{i,t}$ stand for the respective household quantity and updating equation (4) as follows. First, we define $f_t(EX_{i,t})$ and $g_t(x_{i,t})$ to be functions of the respective characteristics of the head of the household, and second, we augment equation (4) so that $g_t(x_{i,t})$ also includes number of members living in the household.

2.2 Moments

Our analysis focuses on how changes to the components of aggregate labour income affect the spread and the tails (asymmetry) of the distribution of idiosyncratic shocks to the corresponding individual measures. We thus calculate, for each annual distribution of the individual (or household) labour income shocks, moments that capture spread and asymmetry. In particular, regarding the spread, we examine the variance of the distribution and the distance between the 90th and the 10th percentile, denoted as $P90/P10$. With respect to asymmetry, we look directly at changes in the tails, as captured by $P90/P50$ and $P50/P10$, and we also calculate the Kelly measure of skewness, which is defined as:

$$Kelly = \frac{(P90 - P50) - (P50 - P10)}{(P90 - P10)}. \tag{5}$$

Note that falls (and vice-versa for rises) in $P90/P50$ of the distribution of labour income shocks, implying a reduction in the size of the right tail, signify a smaller probability of big "positive" shocks, i.e. in shocks that are further to the right of the median. In other words, the mass of the distribution to the right of the median is concentrated closer to the median. At the opposite end, increases (and vice versa for decreases) in $P50/P10$ of the distribution of income shocks, implying an increase in the size of the left tail, denote a higher probability of big "negative" shocks, i.e. in shocks that are further to the left of the median. In other words, the distribution to the left of the median is spread further away from the median. Kelly skewness provides an intuitive summary measure of these possibilities. For example, a reduction in Kelly skewness refers to the case where the left tail of the distribution becomes thicker compared with the right tail, indicating a higher probability of receiving negative, relative to positive, shocks. This makes the Kelly measure useful for the analysis of asymmetries in income shocks and as such has been used in the relevant research (see, e.g. Guvenen *et al.* (2014) and Busch *et al.* (2016)).

An additional advantage of Kelly skewness, compared with, for instance, the usual third moment measure of skewness, is that it is not subject to outliers in the distribution. This point has been highlighted in Guvenen *et al.* (2014) and Busch *et al.* (2016) and is particularly relevant for survey data, like the datasets used here, which may contain extreme values due to reporting and/or other measurement errors.

2.3 Relating idiosyncratic to aggregate shocks

As discussed in the introduction, we are interested in the relationship between the properties of the distributions of idiosyncratic shocks to individual earnings, employment and wages, as well as to household income, to changes at the "aggregate" or "average" level in the labour market. Idiosyncratic labour income risk is approximated by the appropriate moments of the cross-sectional distribution of shocks to $y_{i,t}$ as described above, while, as explained in the next Section, we measure changes at the aggregate level to the respective labour income variable by calculating changes to the average of the labour income measures across individuals.

We adopt two approaches to model the relationship between moments of interest of the distribution of shocks to $y_{i,t}$, which are denoted as $m\left(\Delta y_{i,t}\right)$ or $m\left(\Delta\widehat{\mu}_{i,t}\right)$, for growth rates in $y_{i,t}$ and the residuals $\widehat{\mu}_{i,t}$, respectively, and aggregate changes, which are denoted as ΔY_t. First, we define periods of positive/negative changes in the components of aggregate labour income to be those periods where the annual growth rate of the mean of the relevant measures are positive/negative. We then compare, using a graphical representation, idiosyncratic risk between periods of positive and periods of negative shocks. The graphical analysis serves to provide an overall summary of the key relationships.

However, this approach has the disadvantage of splitting the sample arbitrarily into "good" and "bad" periods at the aggregate level. In particular, there are periods of acceleration or of slowdown in aggregate earnings growth, which could also have a bearing on the distribution at the individual level, irrespective of the actual sign of the growth rate of the aggregate quantity (similar arguments are also made in e.g. Busch *et al.* (2016)).[12] Moreover, changes differ quantitatively, even if their sign is the same. Therefore, there is useful information to exploit when relating quantitative changes at the aggregate level to the properties of the distribution of individual shocks.

In light of the above, we next regress the moment of interest at the indi-

[12] This argument applies of course more generally to any binary classification to "expansionary" or "recessionary" periods.

vidual level on the corresponding aggregate measure of the cycle:

$$m\left(\Delta\widehat{\mu}_{i,t}\right) = \alpha_0 + \alpha_1 t + \gamma \Delta Y_t + u_t \tag{6}$$

where t is a linear time trend. This specification follows Busch *et al.* (2016) and allows us to evaluate more formally the statistical significance of the reaction coefficient γ attached to ΔY_t. Note that we focus on results using $\Delta\widehat{\mu}_{i,t}$, which is a better measure of the idiosyncratic component of risk. However, for completeness and robustness, we also present in Appendix B results obtained by replacing (6) with:

$$m\left(\Delta y_{i,t}\right) = \alpha_0 + \alpha_1 t + \gamma \Delta Y_t + u_t \tag{7}$$

which follows more closely Busch *et al.* (2016) in the choice of income growth as a measure of income shocks.

3 Data

In this section we first provide information on the dataset and variables used for the analysis, and a brief description of the sample selection criteria. Further details on the datasets and the definition and construction of variables can be found in Appendix A. The main datasets used are the British Household Panel Survey (BHPS) and the subsequent Understanding Society Survey, with additional information from the dataset Derived Current and Annual Net Household Income Variables (see Bardasi *et al.* (2012)).

3.1 Sample

The BHPS is a comprehensive longitudinal study for Great Britain, covering 1991 to 2008. It includes information for up to 5000 households on earnings and other sources of income for individuals and households over an annual period starting in September, as well as on socio-economic characteristics of the respondents. These characteristics include gender, education, age, social (professional) class and region.[13] BHPS was replaced in 2010 by a new panel data survey, Understanding Society, which extends the BHPS original sample but also allows us to extend the analysis for wages in a consistent way by using the BHPS sub-sample of Understanding Society up to 2014. Unfortunately,

[13] Data on Northern Ireland are available from 1997 via the additional BHPS sub-sample European Community Household Panel Survey. However, we focus on Great Britain to not restrict further the time dimension, which is important for our analysis.

households were not interviewed in 2009, implying a missing year.[14] We also make use of the auxiliary dataset Derived Current and Annual Net Household Income Variables, compiled by Bardasi *et al.* (2012), which contains derived data on household disposable income. Note that the Bardasi *et al.* (2012) dataset tracks the same individuals/households for the same time as the BHPS i.e. 1991-2008.

3.1.1 Individual level

We employ annual earnings and hourly wages for individuals, both for males and females. We make use of BHPS data for 1991-2008 for annual earnings and for 1991-2008 and 2010-2014 for wages. Regarding wages, the BHPS component of Understanding Society records the same information as BHPS up to 2008, thus guaranteeing consistency. This is not, however, the case for annual earnings, which is recorded directly in BHPS only until 2008.

We present our main results first focusing on labour income risk for male individuals. We also discuss results on female earnings risk, as well as on female employment and wage risk. Given that female labour supply decisions are also significantly affected by non-economic factors or often decided at the household level, we focus on individual level results for males. Nonetheless, we present results for females as they reveal interesting patterns and also inform the analysis of labour income risk at the household level.

To analyse earnings risk for males, we concentrate on individuals who are attached to the labour market. Therefore, in any year, we retain male individuals in the main working age of 25-60 (see also e.g. Busch *et al.* (2016), Guvenen *et al.* (2010), Blundell and Etheridge (2010), Heathcote *et al* (2010)) who report positive annual earnings.[15] To ensure strong attachment to the labour marker, we follow e.g. Guvenen *et al.* (2014), Busch *et al.* (2016) and include in any year individuals who report an annual income greater than half of the product between the minimum legal hourly wage times 520 hours, implying at least a few months of work during the year. Moreover, we also follow these studies and exclude in any year the top 1% of the observations with positive earnings, to avoid extreme cases (e.g. possible outliers in recorded earnings) that may affect results.

[14] Since we are looking at growth rates of earnings variables, or changes in the residual earnings variables, we lose three observations for our statistical analysis.

[15] Note that for all individuals BHPS reports earnings, which reflect labour income, separately from income from other sources, e.g. asset income, savings, etc. For individuals who are self-employed we follow e.g. Heathcote *et al.* (2010) and assume that two thirds of their reported earnings is labour income. We also consider results below focusing only on employed labour.

We then continue the analysis focusing on wage risk for male individuals. In this case, we restrict the sample to employed males with positive typical weekly earnings and construct the hourly wage by dividing by typical hours worked per week (see also e.g. Blundell and Etheridge (2010), using BHPS data). We also trim the top and bottom 0.5% of observations of wages in any year, again to deal with possible outliers in recorded wages. At the lower end, this effectively discards those individuals with less than about half the minimum wage.[16]

To construct a measure for employment, we use BHPS data for 1991-2008 on weeks worked in the year and usual hours of work per week for the corresponding sample of male individuals.[17] The product of these two quantities provides an approximation to hours of work per year for the individual. We drop individuals who have been inactive (i.e. full time students, long term sick/disabled, women on maternity leave) in the labour market for more than 39 weeks, to focus on employment risk as opposed to labour market participation. We also drop individuals with zero hours of employment and those individuals whose responses imply that they worked for more than 84 hours a week.

For the individuals in the sample we have additional information on education, age, social class and region. We also examine separately the group of male individuals who have completed University education and the group of individuals without University education, by splitting the above samples based on this information.[18] When working with the distribution of earnings, employment and wages for females, we follow the same steps as above for males. Further details on the definitions of variables used and on the construction of the dataset are in Appendix A.

3.1.2 Household level

We construct households using BHPS data for 1991-2008 as follows. We start with the allocation of individuals to households from BHPS and keep households with a spouse/partner relationship (hence discarding those that comprise of a single member or those that involve cohabiting but not family-related members) and those where the head is between 25-60 years, and

[16] For other studies which trim their samples in similar ways, see, e.g. Bayer and Juessen (2012), Jenkins (2011), Blundell and Etheridge (2010) and Heathcote *et al.* (2010).

[17] This measure cannot be extended post-2008 consistently, because the sample does not include the information on weeks worked in the year.

[18] When evaluating the results from the two groups, it should be kept in mind that the group of University educated individuals is significantly smaller that the group of non-University educated individuals. Details on sample sizes are given in Appendix A.

reports non-zero labour income.[19] Following e.g. Blundell and Etheridge (2010) we define the head to be the older married (or in partnership) male. We also have measures on earnings of the household's individual members.

To construct household total earnings, we sum individual members' earnings. For this sample, we can obtain data on household gross and disposable income from the Derived Current and Annual Net Household Income Variables dataset. We trim the households in the top 1% of household total earnings and those whose records indicate total earnings below the income threshold defined above, i.e. labour income less than half of the product between the minimum legal hourly wage times 520 hours, implying at least a few months of work during the year for at least one member of the household.

3.2 Aggregate labour market shocks

To approximate changes at the aggregate level, a natural approach is to consider changes to the mean of earnings, employment and wages of all individuals across the sample (see e.g. Busch and Ludwig (2016) who also use mean earnings in Germany to construct a measure of aggregate labour income shocks, to relate to idiosyncratic risk).

As discussed in the introduction, another possible candidate for aggregate shocks would be changes in GDP. This would have the advantage of making the results more comparable to those for the U.S. in e.g. Storesletten *et al.* (2004) and Guvenen *et al.* (2014) and also for relating idiosyncratic earnings shocks to the business cycle. However, as pointed out above, fluctuations in GDP reflect more than aggregate shocks to labour income. This is true in general, but is particularly relevant for our sample, i.e. British data for 1991-2014. In Figure 1 (first subplot), we plot the growth rate of GDP in the UK, and the growth rate of average earnings, of average employment (annual hours worked) and of average wages using the BHPS constructed sample and variables as discussed above.[20] As can be seen, GDP growth does not correlate well with the series for earnings, wages or employment. In particular, the correlation coefficients between the growth rate in GDP and the growth rates of mean hours, wages and earnings are 0.42, 0.29 and 0.10 respectively. As expected, employment is the most cyclical of the three

[19] Some households defined as such have additional members, e.g. other members of family, living in the same household. We also briefly discuss below results for private and public insurance of the increase in risk when including single households in the sample.

[20] Note that for the BHPS and Understanding Society measures, the period of observation refers to an annual cycle starting in September. Hence, year T in Figure 1 refers to annual quantities between September $T-1$ and August in T.

labour market quantities.

[Figure 1 here]

As Figure 1 shows, there are periods of positive output growth when mean earnings, wages and employment fell, and there are also periods of declines in the growth of mean earnings, wages and employment when output growth was increasing. These differences reflect different sources of shocks to labour markets, e.g. changes in labour legislation, or even aggregate shocks which have different effect of output compared with labour income. For instance, capital augmenting technological change, which has been working through our sample period, favouring output by displacing labour in production, or integration in a more globalised economic environment, which again may favour output but hurt wages and employment of lower skilled.[21]

Using GDP growth in equations (6) and (7) we find little evidence of co-movement for idiosyncratic shocks to earnings and wages, as well as for household earnings, with output growth (see also Bayer and Juessen (2012) for the a-cyclical spread of the distributions to wage shocks). However, there is evidence of co-movement for idiosyncratic shocks to hours with output growth, which generally gives similar results to those obtained later using mean employment growth instead of mean output growth. We summarise the results for idiosyncratic shocks to hours with output growth in Appendix C. Therefore, using GDP growth as a measure of the cycle suggests that only idiosyncratic shocks to hours respond to the aggregate state. However, Figure 1 implies that changes in the aggregate state for the labour market need not correlate well with changes in GDP. We need to look beyond GDP for a measure of the cyclical behaviour of the aggregate state in the labour market. Hence, we use the growth rate of mean earnings as a more accurate measure of aggregate earnings shocks, and similarly for wages and employment we use growth in mean wages and employment respectively. When considering income risk at the household level, the aggregate series we use is the growth of mean earnings for males in Figure 1.[22]

3.3 Inequality

In the second subplot in Figure 1 we plot the evolution of inequality in male individual earnings for the period 1991-2008. In particular, for selected

[21] An additional argument that explains a wedge between shocks to output and shocks to labour markets refers to potential sluggish synchronisation of the labour markets with the business cycle (see e.g. Busch and Ludwig (2016)).

[22] We also considered the growth of mean earnings for the head of the households and it provided very similar results.

percentiles we plot the growth in earnings relative to 1991. We focus on percentiles that also feature in the definition of the Kelly measure of skewness. As can be seen, earnings inequality increased in the 1990s, as upper quantiles reported higher earnings growth than lower quantiles. However, since about 2000 the growth rate of lower and upper quantiles is more comparable and has been generally higher than the growth rate of the median. This implies a convergence in the lower part of the distribution, while top earners increased their income even further.[23] What is also very interesting to note in this plot is that in periods of negative mean earnings growth (the grey shaded areas), the fall in earnings growth in the lower quantiles is much more pronounced than the fall in earnings growth in upper quantiles. These indicate that negative shocks to aggregate earnings are related to an increase in inequality. These effects prompted us to further explore, in the following Section, whether negative shocks to aggregate earnings are also related to an increase in idiosyncratic risk. Hence, we examine if negative shocks to aggregate earnings are correlated with increased uncertainty and an increase in probability of negative earnings shocks at the individual level.

In the third subplot in Figure 1 we plot the evolution of male wages since 1991. In particular, for selected percentiles we plot the growth in wages relative to 1991. The grey shaded areas refer to periods of negative mean wage growth. As can be seen, inequality has increased over time, as upper quantiles report higher earnings growth than lower quantiles, so that the gap is widening over time and in fact wage inequality has increased after the 2008 recession (see, also Fernández-Macías and Vacas-Soriano (2015) who report increase in wage inequality in UK for the years following the financial crisis.). The difference between higher and lower percentiles of the distribution regarding the fall in the growth rate of wages in the grey shaded areas is not as pronounced for wages as it is for earnings, but there are differences across the distribution, and this again motivates us to more systematically analyse whether idiosyncratic wages shocks are related to aggregate shocks to wages.

4 Idiosyncratic risk and the labour market

In this section we first analyse results regarding earnings risk, and for its components. Then, in the second and third sub-section, we examine employment and wage risk respectively. Finally, in the last sub-section, we examine household-level risk and focus on private and public insurance.

[23] For similar findings, see www.gov.uk/ government/statistics/uk-wages-over-the-past-four-decades-2014)

4.1 Earnings risk

We start by analysing the response of earnings risk to shocks to average earnings, using annual earnings data for males and females for the period 1991-2008.[24]

4.1.1 Graphical analysis

By working as discussed in Section 2, we use the distribution of the growth rate in earnings directly and examine the distribution of $\Delta y_{i,t}$ and its relationship with ΔY_t. In Figure 2 (subplot (1,1), we plot the de-trended Kelly skewness for $\Delta y_{i,t}$ against time for the whole sample of males, for the education sub-samples and for females.[25] For all groups, ΔY_t refers to the growth rate of mean earnings for males, since we found that the distribution of female earnings shocks does not respond to changes in mean female earnings, indicating that to a large extent female earnings are viewed as complementing male earnings, an issue we revisit under household insurance. The grey shaded periods refer to periods of ΔY_t.

[Figure 2 here]

As can be seen, periods of negative ΔY_t are associated with a reduction in the Kelly measure, implying an increase in the proportion of the individuals who experienced very low earnings shocks, relative to those who experienced very positive earnings shocks. In other words, there is an increase in the probability that an individual receives an earnings shock at the lower end of the distribution, and/or a reduction in the probability that an individual receives a shock at the upper end of the distribution. We decompose these two effects further in Figure C.1 in Appendix C, where we plot for male individuals the 10th, 50th and 90th percentile of the distribution of $\Delta y_{i,t}$, for individual earnings, employment (annual hours), and wages (effective hourly wage). This helps to contextualise the magnitude of the shocks across the distribution and also demonstrates the two factors driving the reduction in Kelly skewness in periods of negative ΔY_t . In particular, as can be seen in the grey shaded areas of subplot (1,1) in Figure C.1, the distance between the 50th and the 10th percentile of earnings shocks increases, while the distance between the 90th and the 50th percentile decreases.

[24] Since we focus below on the sample of males that partially includes earnings of the self-employed, we also checked our results using: (i) only the employed individuals; (ii) all of the self-employed earnings. The main results reported here do not change.

[25] In particular, for each moment plotted in the Figures, we regress the moment against a linear trend and plot the residuals centered around the average of the moment over time.

In Figure 2 (subplot (2,1), we plot the de-trended variance for $\Delta y_{i,t}$ against time, and as can be seen an increase/reduction is not as clear, at least for the males (we return to female variance in the next sub-section). Moreover, while skewness is volatile over time, the variance is relatively stable (the latter result is also consistent with the findings in Cappellari and Jenkins (2014)). These results indicate that periods of negative earnings shocks, as measured by negative growth of average earnings, are associated with a drop in Kelly's skewness. However, the spread of the distribution is not higher, as intuition would perhaps suggest. These findings summarise, for Great Britain, the main results in previous research for the U.S. and also Germany and Sweden in Guvenen *et al.* (2014) and Busch *et al.* (2016). In particular, that in response to negative aggregate shocks, positive skewness of the shocks to individual earnings decreases, while the variance does not change.

To partial out the effect of observables and better identify idiosyncratic earnings risk, we then work as analysed in Section 2 and use the distribution of the growth rate of residual earnings. In this case we examine the distribution of $\Delta\widehat{\mu}_{i,t}$ and its relationship with ΔY_t. We look at the same groups as above. In Figure 2 (subplots (1,2) and (2,2)), we plot the de-trended Kelly skewness and the de-trended variance for $\Delta\widehat{\mu}_{i,t}$ against time. The results are broadly similar with those for the moments of the distribution of $\Delta y_{i,t}$, i.e. the skewness of $\Delta\widehat{\mu}_{i,t}$ drops with ΔY_t, but its variance does not increase for males.

4.1.2 Co-movement

A more general approach to relate the properties of the distribution of idiosyncratic earnings shocks, as measured by residual earnings growth, to changes in aggregate earnings is to exploit all the variation in ΔY_t and in $m\left(\Delta\widehat{\mu}_{i,t}\right)$, using equation (6). In Table 1, we summarise the coefficient estimates, $\widehat{\gamma}$, for ΔY_t in regressions for $m\left(\Delta\widehat{\mu}_{i,t}\right)$, and denote their significance (in terms of p-values), for all five samples described above. We also report the $p-$value of Durbin's F-test for serial correlation.[26]

The regression results confirm what Figure 1 suggested. In particular, focusing on males, the relationship between ΔY_t and neither the variance of the distribution of $\Delta\widehat{\mu}_{i,t}$, nor $P90/P10$, is significant. However, for all groups of males individuals, a reduction in ΔY_t results in a decrease in Kelly skewness of the distribution of $\Delta\widehat{\mu}_{i,t}$, which implies that the probability (or proportion) of earnings shocks at the lower end of the distribution, relative

[26]Other than variance for females, which will be discussed below, the serial correlation test only rejects the null in cases where the $\widehat{\gamma}$ coefficient is not significant.

to that of shocks at the upper end, increases at the individual level. This is further confirmed by looking at the effects of ΔY_t on $P90/P50$ and $P50/P10$, which both have consistent signs with this interpretation. In particular, the coefficient for the $P50/P10$ regressions is negative and significant, suggesting that when aggregate conditions worsen, the negative earnings changes are more likely. On the other hand, while the coefficient for the $P90/P50$ regressions is positive in all samples, it is not significant.

Table 1: Moment Regressions, residual earnings growth

	Variance	Kelly	P90/50	P50/10	P90/10
			Males		
$\widehat{\gamma}$ coef.	0.130	3.059	0.839	-0.695	0.144
pval. $\widehat{\gamma}$	0.530	**0.020**	0.189	**0.054**	0.855
pval. D.W.	0.690	0.184	**0.053**	0.371	**0.066**
			University educated males		
$\widehat{\gamma}$ coef.	0.009	4.529	0.767	-1.387	-0.621
pval. $\widehat{\gamma}$	0.986	**0.011**	0.331	**0.004**	0.484
pval. D.W.	0.643	0.436	0.118	0.399	0.377
			Non-university educated males		
$\widehat{\gamma}$ coef.	0.202	3.265	0.890	-0.740	0.149
pval. $\widehat{\gamma}$	0.356	**0.009**	0.124	**0.034**	0.834
pval. D.W.	0.940	0.636	0.277	0.191	0.108
			Females		
$\widehat{\gamma}$ coef.	0.396	2.679	1.234	-0.444	0.790
pval. $\widehat{\gamma}$	**0.095**	**0.020**	**0.033**	0.366	0.336
pval. D.W.	**0.036**	0.233	0.967	0.178	**0.037**

Note: bolded values indicate significance at the 10% level or less in all tables reported in the paper.

To summarise, in Great Britain, skewness for males decreases with aggregate shocks to earnings, while variance does not change, consistent with the main result in Guvenen *et al.* (2014), Busch *et al.* (2016) for Germany, Sweden and the U.S.. However, some results here are different than in these studies. In particular, while results from earnings growth suggest that the change in skewness is also driven by a contraction of the upper tail (i.e. a reduction in the probability of positive shocks), the effect seems to be primarily driven by an expansion of the lower tail, i.e. an increase in the probability of very bad earnings shocks in downturns.

The results for $m\left(\Delta y_{i,t}\right)$ from equation (7) are in Appendix B, Table B.1. It is worthwhile noting that the results regarding variance, Kelly skewness and $P50/P10$ are robust to using moments for $\Delta y_{i,t}$ instead of $\Delta\widehat{\mu}_{i,t}$

(an exception is the coefficient for $P50/P10$ for University educated males, which loses its significance). Using $\Delta y_{i,t}$ instead of $\Delta\widehat{\mu}_{i,t}$, it also appears that the coefficient for the $P90/P50$ regressions is positive. However, the serial correlation test rejects in these cases, suggesting mispecified error term dynamics which may affect the estimated relationship between $P90/P50$ and ΔY_t. Given that the residual growth regressions using $\Delta\widehat{\mu}_{i,t}$ do not indicate serial correlation, it is reasonable to assume that these ignored earnings dynamics are changes in observables that have not been controlled for.

Finally, the results for female earnings risk are also in line with Busch *et al.* (2016) for Germany, Sweden and the U.S.. In particular, Kelly skewness is positively correlated with ΔY_t (although now the coefficient for the $P90/P50$ regressions is significant). Interestingly, the variance is also positively related with ΔY_t, again similar to Busch *et al.* (2016). A positive coefficient implies that female earnings are more spread out in better times. For instance, this could be explained if female earnings are viewed within the household as a secondary source of income. In this case, periods of better labour market conditions offer more opportunities for workers to spread out on the distribution (e.g. some female individuals may take low paid jobs or part-time and some will not, depending on the valuation of non-work time). Whereas, in bad times, choice is restricted by market availability and household needs, leading to a clustering near the mean. In particular, when male earnings are reduced, there is an incentive for females to increase their contribution to smooth household consumption. Thus, focusing on more standard jobs with smaller variation in earnings. These results will be revisited below. At this stage, the specific result for female earnings variance in Table 1 should be treated with caution, since the serial correlation test for this regression rejects the null. This likely reflects the importance of social factors determining female labour supply, which have not been adequately controlled for by our available measures of observables.

4.1.3 Wage vs employment risk

Earnings risk reflects risk to the time input (hours of work) and to the return to the time input (hourly return). To see whether similar patterns are observed in these two components of earnings risk, we construct a sample that consistently measures annual earnings, annual hours of work and hourly returns, based on the sample for annual earnings for male individuals that was used in Table 1. In particular, starting from that sample, we retain only observations for which information exists to construct positive annual hours worked (i.e. multiplying weeks worked in the year by hours of work per week). We then construct the hourly rate by dividing annual earnings by annual hours, and trim the top and bottom 0.5% of the sample according to the distribution of the hourly return, to discard potential outliers. We summarise, in Table 2 the results from the regression analysis using equation (6) for $m\left(\Delta\widehat{\mu}_{i,t}\right)$, for annual earnings, annual hours and the hourly return on this sample. The results for $m\left(\Delta y_{i,t}\right)$ from equation (7) are in Appendix B, Table B.2. In each case, we examine the relationship of the moments of the relative distribution with the growth rate in mean annual earnings (the series used in Figure 1), which we use as a proxy for shocks to aggregate earnings. Hence, the right-hand side variable in all regressions in Table 2 is ΔY_t from the previous sub-section.

Table 2: Moment Regressions, sources of earnings risk

	Variance	Kelly	P90/50	P50/10	P90/10
	Residual earnings growth				
$\widehat{\gamma}$ coef.	0.136	2.928	0.840	-0.516	0.324
pval. $\widehat{\gamma}$	0.339	**0.018**	0.180	0.137	0.695
pval. D.W.	0.721	0.662	**0.046**	0.109	**0.011**
	Residual annual hours growth				
$\widehat{\gamma}$ coef.	-0.146	-0.778	0.003	0.181	0.184
pval. $\widehat{\gamma}$	0.273	0.425	0.984	0.145	0.246
pval. D.W.	0.159	0.848	0.685	0.710	0.262
	Residual hourly return growth				
$\widehat{\gamma}$ coef.	0.035	2.665	0.721	-0.591	0.130
pval. $\widehat{\gamma}$	0.729	**0.036**	0.228	**0.086**	0.856
pval. D.W.	0.338	0.598	0.280	0.382	**0.020**

The results in Table 2 first confirm for this smaller sample the main result in Table 1, i.e. that Kelly skewness is positive and significant for male annual earnings. The coefficient for the $P50/P10$ regressions is negative but not significant, which is not surprising because we have discarded even more tail observations in this experiment, by also excluding the top and bottom changes in the hourly return. Hence, although the tails of the distribution do not change significantly on their own with ΔY_t in this sample with fewer tail observations, jointly they vary with ΔY_t so that their relative change is significant.

The main result in Table 2 is that the changes in the distribution of annual earnings are driven by changes in the return to labour (hourly return), and not in the labour input (annual hours). In particular, the results for the hourly return in Table 2 are very similar to those for annual earnings in Table 1, while moments for annual hours do not have significant relationships with the growth rate in annual earnings. These results are consistent with those reported in Guvenen *et al.* (2014, Appendix B), who also report a-cyclicality of annual hours for the sample of individuals for whom annual earnings display a counter-cyclical left skewness of earnings growth.

Here we examined the relationship between annual hours and the hourly return with mean earnings growth for workers with some annual income and hours of work during the year. Our aim was to look beyond earnings risk (for individuals who have at least some employment and earnings) to see which source of earnings risk matters the most. The consistency in the sample used, in terms of the definitions of annual hours and hourly return with earnings, as well as in having a common ΔY_t, allowed us to do that. However, since our sample effectively contains workers with at least a few months of work in the year, annual hours risk in Table 2 does not fully take into account the risk of unemployment, which is obviously a major source of income risk for some individuals. Similarly, our measure of the hourly return is an effective measure over the year and may not be a good approximation to the hourly wage.[27] Moreover, as the analysis in Figure 1 showed, changes in mean earnings are not equivalent to changes in mean employment or changes in mean wages. Hence, the results in Table 2 may not fully capture idiosyncratic employment and wage risk and in particular their relationship with changes in aggregate employment and wages. Our analysis in the next sub-sections demonstrates this point.

4.2 Employment risk

We next analyse employment risk by using annual hours as described in Section 3.

4.2.1 Graphical analysis

First, by working as discussed in Section 2, we use the distribution of the growth rate in employment directly and we examine the distribution of $\Delta y_{i,t}$ and its relationship with the growth rate in aggregate employment, ΔY_t. In Figure 3 (subplot (1,1), we plot the de-trended Kelly skewness for $\Delta y_{i,t}$ against time for the whole sample of males, for the education sub-samples and for females. In subplot (1,2), we plot the variance for $\Delta y_{i,t}$ against time. We then use the distribution of the growth rates of residual employment and in subplots (1,2) and (2,2) we plot the Kelly skewness and the variance for $\Delta \widehat{\mu}_{i,t}$ against time. For all groups, ΔY_t refers to the growth rate of mean

[27] In Section 3 we described how we constructed series to allow us to look into employment risk (which better captures risk of unemployment), and into wage risk (constructed as an effective wage using weekly information).

employment for males. The grey shaded periods refer to periods of negative employment growth at the aggregate level.

[Figure 3 here]

As can be seen, patterns are less pronounced compared with those for earnings. Overall, it seems that periods of negative ΔY_t are associated with a reduction in the Kelly measure, implying an increase in the probability that an individual receives negative, relative to positive, employment shocks (see also Appendix C, Figure C.1, subplot (1,2)). Moreover, there seems to be a fall in the variance in periods of negative ΔY_t, implying a smaller spread in employment when there is negative growth in mean employment. However, the classification to positive and negative aggregate growth here does not produce clear patterns. To exploit all the variation in ΔY_t and in $m\left(\Delta\widehat{\mu}_{i,t}\right)$ we use equation (6) and present these results below.

4.2.2 Co-movement

We summarise, in Table 3, the results from the regression analysis using equation (6) for $m\left(\Delta\widehat{\mu}_{i,t}\right)$, for employment. The results for $m\left(\Delta y_{i,t}\right)$ from equation (7) are in Appendix B, Table B.3.

The results in Table 3 show that, regarding employment risk for males, Kelly skewness is significantly positively related to aggregate shocks, and it is predominantly changes in the low tail that matter. The result that there is increased idiosyncratic employment risk in periods of negative developments at the aggregate level is consistent with the findings in Blass-Hoffmann and Malacrino (2016) for Italy and the U.S. Note that in the sample used for Table 3, a large part of movements in and out of employment are included in calculating employment risk, since individuals are included in the sample as long as they have worked for at least one hour during the year (so that only long-term unemployed are excluded). In contrast, for earnings risk in the previous section a strong form of movements in and out of unemployment is excluded, since the analysis effectively focused on individuals who have earnings equivalent to at least a few months of employment during the year. This reinforces the importance of the main results for earnings in Table 1. In other words, these suggest that earnings risk increases with negative aggregate shocks, beyond the effect that the latter may have on long spells of unemployment.

Table 3: Moment Regressions, residual hours growth

	Variance	Kelly	P90/50	P50/10	P90/10
			Males		
$\widehat{\gamma}$ coef.	0.725	6.315	0.813	-0.941	-0.128
pval. $\widehat{\gamma}$	**0.048**	**0.023**	0.113	**0.046**	0.828
pval. D.W.	0.628	0.278	0.115	0.994	0.454
			University educated males		
$\widehat{\gamma}$ coef.	-1.809	-4.474	-3.170	-1.744	-4.914
pval. $\widehat{\gamma}$	0.157	0.310	**0.002**	**0.063**	**0.000**
pval. D.W.	0.516	0.466	0.678	0.641	0.888
			Non-university educated males		
$\widehat{\gamma}$ coef.	1.146	7.617	1.289	-0.844	0.445
pval. $\widehat{\gamma}$	**0.037**	**0.005**	**0.026**	**0.056**	0.511
pval. D.W.	0.498	0.315	0.489	0.554	0.603
			Females		
$\widehat{\gamma}$ coef.	0.434	6.367	2.540	-0.945	1.595
pval. $\widehat{\gamma}$	0.430	**0.012**	**0.033**	0.155	0.228
pval. D.W.	0.859	0.829	0.997	0.134	0.748

In contrast to annual earnings in Table 1, the variance of the distribution of idiosyncratic shocks in employment increases with positive aggregate shocks for employment. This suggests that when there is positive employment growth at the aggregate level, implying more job opportunities for workers, individuals spread out more on the employment distribution. On the other hand, in periods of reductions in aggregate employment, demand is more important in determining equilibrium outcomes and the variation arising from idiosyncratic labour supply is less important. As a result, there is less variation in employment across individuals and the spread of the distribution of employment decreases with negative shocks to aggregate employment.

These results appear to be driven by the responses of employment from non-University educated workers, since the coefficients for variance, skewness and $P50/P10$ have the same sign and significance for this group as for the whole sample. Moreover, for this group, $P90/P50$ is also significant, with a positive sign, suggesting that in periods of reduced employment growth at the aggregate level, the probability that non-University educated workers will increase their annual hours significantly is reduced.

Interestingly, this result is reversed for University educated workers. For them, periods of reductions in mean employment growth are periods where it is more likely to increase significantly work hours. This could reflect an increase in work hours in such periods if firms find it optimal to increase employment/overtime of skilled labour as opposed to hiring unskilled labour. The combined effect of $P90/P50$ for University and non-University workers may thus suggest that in periods of worsening of aggregate conditions for employment, skilled workers are required to or are used to do some of the work of unskilled workers. Because $P90/P50$ also has a negative sign, despite the negative sign in $P50/P10$, the distribution for employment for University workers does not change in terms of symmetry of the tails with mean employment growth, i.e. both tails contract and expand together. On the other hand, this effect underlies the increase in the dispersion of the distribution when aggregate conditions worsen (see the coefficient in $P90/P10$).

Finally, the results suggest that female employment risk has overall similar properties with male employment risk regarding asymmetry. Note that the right-hand side variable in the regression for female employment moments is the growth rate of mean male employment, since it captures better overall changes in employment in the labour market.

4.3 Wage risk

To analyse wage risk we can exploit the information post-2008 available from the BHPS subset of Understanding Society. This allows us to use more years and, importantly, more years with negative aggregate wage growth (see Figure 1). We therefore continue by analysing the response of wage risk to shocks to average wages, using data for male's wages for the period 1991-2014.

4.3.1 Graphical analysis

First, by working as discussed in Section 2, we use the distribution of the growth rate in wages and we examine the distribution of $\Delta y_{i,t}$ and its relationship with ΔY_t. In Figure 4 (subplot (1,1), we plot the de-trended Kelly skewness for $\Delta y_{i,t}$ against time for the whole sample of males, for the education sub-samples and for females. For all groups, ΔY_t refers to the growth rate of mean wages for males. The grey shaded periods refer to periods of negative wage growth at the aggregate level. As can be seen, periods of negative ΔY_t are associated with a reduction in the Kelly measure, implying an increase in the probability that an individual receives a lower wage shock (see also Appendix C, Figure C.1, subplot (1,3)). In Figure 4 (subplot (1,2)), we plot the variance for $\Delta y_{i,t}$ against time. A pattern is not as clear, but there are periods of negative wage growth accompanied by an increase in variance.

[Figure 4 here]

To partial out the effect of observables and focus on residual wage risk, we use the distribution of the growth rate of residual wages. In this case we look at the distribution of $\Delta\widehat{\mu}_{i,t}$ and its relationship with ΔY_t. In Figure 4 (subplots (1,2) and (2,2)), we plot the Kelly skewness and the variance for $\Delta\widehat{\mu}_{i,t}$ against time. The results are broadly similar with those for the moments of the distribution of $\Delta y_{i,t}$. The observed properties of skewness is consistent with the results in Busch *et al.* (2016) for Germany, who, nevertheless, do not find a significant pattern for variance. In this sense, the observed properties of variance are closer to the theoretical literature that relates the spread of the distribution of shocks to components of earnings to the aggregate state of the economy, which was reviewed in the Introduction, and thus closer to empirical findings in Storesletten *et al.* (2004).

Finally, the plots in Figure 4 suggest that the observed patterns are not as clear for females and for University educated males, implying that wage risk is affecting mainly non-University educated workers. To further investigate the relationship between changes in aggregate wages and idiosyncratic wage risk, we exploit all the variation in ΔY_t and in $m\left(\Delta\widehat{\mu}_{i,t}\right)$, using equation (6).

4.3.2 Co-movement

We summarise the results from the regression analysis using equation (6) for $m\left(\Delta\widehat{\mu}_{i,t}\right)$ for wages using the extended sample 1991-2014 in Table 4.[28] These show that Kelly skewness increases significantly with positive effects to aggregate wages (suggesting that left-skewness increases with reductions in the growth rate of aggregate wages). Moreover, the changes in the symmetry of the distribution are predominantly driven by changes in the upper tail. Hence, with reductions in mean wage growth, larger idiosyncratic wage rises are less likely.

The change in the upper tail (i.e. in $P90/P50$) also applies to the sample of non-University educated workers, for which changes in skewness are also significant. Note also that for non-University educated workers, the change in the lower tail (i.e. in $P50/P10$) is significant when we look at $m\left(\Delta y_{i,t}\right)$ from equation (7), see Appendix B, Table B.4. In contrast, no moments for the sample of University educated workers seems to be significantly related to mean wage growth. We conclude therefore that wage risk increases with negative effects on mean wages, and this affects the lower skilled workers.

[28] These regressions include a dummy variable for the years after 2009, to account for the consistently higher variance for this period. The main results are not affected by the inclusion or not of this dummy variable, but the serial correlation coefficient for variance rejects the null of no serial correlation in the error term when the persistent higher variance post 2009 is not accounted for in the regression.

For males, the variance of residual wage growth increases when the growth of aggregate wages falls, reflecting a increase in uncertainty in periods of lower mean wage growth. However, for the females, wage variance tends to be higher in periods of expansion of aggregate wages for the males (see the coefficient in $P90/P10$ but also the coefficient for variance is only marginally insignificant). As was discussed earlier under the results for earnings, this could reflect a form household insurance. In periods of reduction of male wages (typically the head of the household), females may have an incentive to cluster around more standard jobs with less spread-out or risky returns, to increase their contribution to household income. We take up household insurance directly in the next sub-section. Finally note that for females the change in the upper tail (i.e. in $P90/P50$) is significant when we look at $m(\Delta y_{i,t})$ from equation (7), see Appendix B, Table B.4 (and is only marginally insignificant in Table 4 here).

Table 4: Moment Regressions, residual wage growth

	Variance	Kelly	P90/50	P50/10	P90/10
			Males		
$\widehat{\gamma}$ coef.	-0.105	1.395	0.384	-0.256	0.127
pval. $\widehat{\gamma}$	**0.042**	**0.042**	**0.036**	0.165	0.521
pval. D.W.	0.966	0.667	0.554	0.908	0.854
			University educated males		
$\widehat{\gamma}$ coef.	-0.101	-0.344	-0.128	0.023	-0.105
pval. $\widehat{\gamma}$	0.307	0.793	0.725	0.934	0.717
pval. D.W.	0.278	0.436	0.964	**0.098**	0.927
			Non-university educated males		
$\widehat{\gamma}$ coef.	-0.113	1.717	0.570	-0.242	0.329
pval. $\widehat{\gamma}$	0.101	**0.008**	**0.002**	0.187	0.145
pval. D.W.	0.879	0.381	0.873	0.287	0.776
			Females		
$\widehat{\gamma}$ coef.	0.149	-0.018	0.227	0.217	0.444
pval. $\widehat{\gamma}$	0.101	0.973	0.104	0.190	**0.014**
pval. D.W.	0.763	**0.034**	0.999	**0.043**	0.475

4.4 Household income risk

We finally analyse income risk at the household level. We focus on three questions, namely whether there is evidence of within-household insurance, whether there is evidence of private insurance to earnings shocks and whether there is evidence of public insurance to household income.

To answer the first question, we look at household earnings, constructed as described in Section 2, and compare household earnings risk to earnings risk for the members of the household. In particular, we examine whether the relationship between the moments of the distribution of residual growth in earnings and mean growth in earnings differs between individuals and households. Evidence of household insurance would take the form of a lower increase in household earnings risk, compared with that for the individual, in periods of lower mean earnings growth for the individual. To answer the second question, we examine the moments of the distribution of residual growth in household earnings and the moments of the distribution of residual growth in household gross income. If the latter indicate that household gross income risk (i.e. the probability of receiving negative income shocks) increases less than household earnings risk, when aggregate conditions worsen, then there is evidence that households use non-labour income to smooth shocks to earnings. Finally, to answer the last question, we examine the moments of the distribution of residual growth in household gross income and the moments of the distribution of residual growth in household net income. If the latter indicate that household net income risk increases less than household gross income risk, when aggregate conditions worsen, then there is evidence that public policy smooths shocks to household income. We also look at household earnings plus private and public transfers (benefits), which provides a measure of pre-tax labour income available to the household and may thus capture better the total household labour income (similar measures of household labour income have been used in e.g. Storesletten *et al.* (2004)).

Given the above, we focus on five income measures, namely household total earnings, head of the household earnings, spouse earnings, household gross income, household earnings plus benefits, and household net income. We first use the distribution of the growth rate in each measure of equivalised household income and we examine the distribution of $\Delta y_{i,t}$ and its relationship with ΔY_t. We then look at the distribution of the residual growth rate in each measure and we examine the distribution of $\Delta\widehat{\mu}_{i,t}$ and its relationship with ΔY_t. For all measures, ΔY_t refers to the growth rate of mean earnings for males (i.e. the series in Figure 1), thus providing a common base of earnings shocks to which the different measures of household income risk respond to.[29]

4.4.1 Graphical analysis

In Figure 5 (subplot (1,1)), we plot the de-trended Kelly skewness for $\Delta y_{i,t}$ against time for household total earnings and the member earnings, to inves-

[29]As in analysis in previous sections, the distributions do not exhibit co-movement with changes in aggregate female earnings.

tigate within-household insurance. The grey shaded periods refer to periods of negative mean earnings growth for males. In subplot (1,2), we plot the variance for $\Delta y_{i,t}$ against time, whereas in (subplots (1,2) and (2,2)) we plot the Kelly skewness and the variance for $\Delta\widehat{\mu}_{i,t}$ against time. In Appendix C, Figure C.3, we plot the relevant moments for household total earnings together with different household income measures, to investigate the effect of private and public insurance.

[Figure 5 here]

Regarding skewness, in can be seen in Figure 5 that it is lower and it drops relatively less in the grey shaded areas for household total earnings, compared with head and spouse earnings. There are also differences in Figure C.2 between household earnings and household gross and net income. In Appendix C, Figure C.3 we plot the 10th, 50th and 90th percentile of the distribution of $\Delta y_{i,t}$, for equivalised household labour income, gross income and disposable income. Again, differences in the grey shaded areas in the distances between the percentiles are not as clear, especially for gross and disposable income since they move more closely together. Regarding variance, the ranking of the levels of variance suggests smoothing from members to households and from household earnings to household gross and net income. In particular, the spread of the distributions is consistently smaller for the household compared with its members, similar for gross household income and household earnings, and lower for net household earnings. There is not a clear pattern in variance over time.

4.4.2 Co-movement

To further investigate the relationship between household income risk and aggregate conditions, we summarise the results from the regression analysis using equation (6) for $m\left(\Delta\widehat{\mu}_{i,t}\right)$ for the household income measures in Table 5. We first note that the coefficient for the relationship of Kelly skewness with mean earnings growth is smaller for household earnings, compared with male (head) earnings (the reduction is bigger, and applies to both members of the couple, when looking at the results in Appendix Table B.5). Moreover, there is a reduction in the coefficient for the upper tail, especially when comparing the effect for female spouse earnings with that household total earnings. On the other hand, for the lower tail, there is no evidence of reduction when moving from male head earnings to household total earnings.

Secondly, there is evidence of both private and public insurance in periods of worsening aggregate conditions, in the sense that the increase in household income risk is smaller for gross income compared to earnings, smaller for earnings plus benefits and even smaller for net income. The increase in Kelly remains significant for earnings plus benefits, but, when looking at net income, the increase in Kelly is not statistically significant in Table 5 (although the coefficient is significant in Appendix, B Table B.5). The results from the different household income measures suggest that households use non-labour sources of income to reduce large negative income shocks in periods of reduced mean earnings, and that government policy smooths such shocks even further.

Table 5: Moment Regressions,
residual household earnings/income growth

	Variance	Kelly	P90/50	P50/10	P90/10
			Total earnings		
$\widehat{\gamma}$ coef.	0.019	1.937	0.413	-0.596	-0.183
pval. $\widehat{\gamma}$	0.894	**0.005**	0.201	**0.015**	0.690
pval. D.W.	0.938	0.278	0.151	0.583	0.248
			Head earnings		
$\widehat{\gamma}$ coef.	-0.056	2.335	0.597	-0.531	0.066
pval. $\widehat{\gamma}$	0.880	**0.073**	0.417	0.113	0.941
pval. D.W.	0.926	0.725	0.407	0.347	0.227
			Spouse earnings		
$\widehat{\gamma}$ coef.	3.181	1.690	1.678	0.238	1.916
pval. $\widehat{\gamma}$	**0.019**	0.140	**0.016**	0.727	**0.055**
pval. D.W.	0.424	0.844	0.889	0.861	0.760
			Gross income		
$\widehat{\gamma}$ coef.	0.041	1.531	0.410	-0.396	0.014
pval. $\widehat{\gamma}$	0.769	**0.041**	0.218	**0.097**	0.974
pval. D.W.	0.901	0.285	**0.020**	0.736	**0.058**
			Earnings plus benefits		
$\widehat{\gamma}$ coef.	0.051	1.319	0.402	-0.216	0.186
pval. $\widehat{\gamma}$	0.529	**0.064**	0.145	0.243	0.575
pval. D.W.	0.623	0.602	0.343	0.610	0.257
			Net income		
$\widehat{\gamma}$ coef.	0.011	0.699	0.200	-0.123	0.077
pval. $\widehat{\gamma}$	0.833	0.170	0.330	0.462	0.794
pval. D.W.	0.664	0.901	**0.100**	0.298	0.589

We next examine differences in the ability of the households to reduce the effect of large negative earnings shocks depending on whether the head of the household has obtained a University degree or not. The results are summarised in Table 6.

Table 6: Moment Regressions,
residual household income growth, by education

	Variance	Kelly	P90/50	P50/10	P90/10
	Total earnings university educated				
$\widehat{\gamma}$ coef.	-0.388	2.966	0.031	-1.504	-1.474
pval. $\widehat{\gamma}$	0.296	**0.036**	0.959	**0.006**	0.104
pval. D.W.	0.469	0.837	0.161	0.860	0.226
	Gross income university educated				
$\widehat{\gamma}$ coef.	-0.333	2.122	-0.002	-1.073	-1.075
pval. $\widehat{\gamma}$	0.260	**0.091**	0.997	**0.057**	0.231
pval. D.W.	0.391	0.410	**0.061**	0.521	0.120
	Earnings plus benefits university educated				
$\widehat{\gamma}$ coef.	-0.339	2.802	-0.128	-1.547	-1.675
pval. $\widehat{\gamma}$	0.182	**0.043**	0.808	**0.007**	**0.055**
pval. D.W.	0.729	0.834	0.141	0.741	0.156
	Net income university educated				
$\widehat{\gamma}$ coef.	-0.273	1.091	0.099	-0.354	-0.255
pval. $\widehat{\gamma}$	**0.068**	0.369	0.830	0.445	0.710
pval. D.W.	0.533	0.382	0.523	0.941	0.159
	Total earnings non-university educated				
$\widehat{\gamma}$ coef.	0.133	1.724	0.581	-0.302	0.280
pval. $\widehat{\gamma}$	0.322	**0.022**	**0.066**	0.300	0.552
pval. D.W.	0.867	0.565	0.514	0.808	0.336
	Gross income non-university educated				
$\widehat{\gamma}$ coef.	0.142	1.713	0.633	-0.270	0.364
pval. $\widehat{\gamma}$	0.275	**0.030**	**0.056**	0.267	0.377
pval. D.W.	0.912	0.839	**0.063**	0.576	**0.078**
	Earnings plus benefits non-university educated				
$\widehat{\gamma}$ coef.	0.155	1.201	0.513	-0.058	0.455
pval. $\widehat{\gamma}$	0.149	0.127	**0.076**	0.758	0.141
pval. D.W.	0.969	0.384	0.743	0.381	0.265
	Net income non-university educated				
$\widehat{\gamma}$ coef.	0.090	1.112	0.421	-0.090	0.332
pval. $\widehat{\gamma}$	0.158	**0.042**	**0.063**	0.586	0.286
pval. D.W.	0.724	0.623	**0.092**	0.295	**0.242**

Evidence of private and public insurance exists in both educational groups. However, there are also differences, primarily when evaluating the effect of government policy. In particular, for the University educated group, moving from gross income to net income reduces the increase in income risk by a large amount and, in fact, in terms of disposable income, the probability of large negative income shocks is not significant (although the coefficient for $P50/P10$ is significant in Appendix B Table B.6). Furthermore, the variance of the distribution of net income shocks increases in periods of a reduction of mean earnings. In contrast, for households whose head is non-University educated, moving from earnings to gross income has very little effect on the Kelly coefficient. The latter is reduced when moving to disposable income, but remains significant. Moreover, the variance of the distribution of net income shocks is not affected by changes in mean earnings (if anything, the sign is positive).

The results in Table 6 (as well as in Appendix Table B.6) show that for households whose head is University educated, the increase in idiosyncratic risk in labour and gross income takes mainly the form of an expansion of the lower tail when the labour market contracts. On the other hand, for households whose head is not University educated, changes in the upper tail seem to be an important part of the story. As can be seen, the relevant coefficients are always significant in Table 6 and in most cases as well in Appendix Table B.6. However, it should be noted that the results also indicate potential serial correlation in some case. Therefore some caution is needed for the $P90/P50$ regressions. Moreover, for this group of households, the coefficients for $P50/P10$ are significant in Appendix Table B.6, but not in Table 6. Therefore, for households whose head is not University educated, it seems that changes in both tails contribute to the increase in left-skewness in periods of reduced mean earnings, the combined effect being more important than the individual effects.

To summarise, there is evidence for stronger effects of private insurance for households whose head is University educated compared with households whose head does not have a University degree, suggesting a reduced ability for the latter households to smooth negative earnings shocks using asset income. Moreover, for households whose head is University educated, it is mainly the overall spread of the distribution of disposable income that increases with reductions in mean earnings, whereas changes in the left-skewness of the distribution of disposable income become less pronounced. In contrast, for households whose head is not University educated, the overall spread of the distribution of disposable income does not increase with reductions in mean earnings. However, changes in the left-skewness of the distribution of disposable income remain significant, even if quantitatively reduced.[30]

[30] We also examined private and public insurance for an increase in risk when including single households in the sample. The main results do not change. Namely, there is still evidence of private and public insurance, although the increase in Kelly is not eliminated when looking at disposable income. Moreover, the effects on household income risk are

The difference in the effect of government policy, regarding the reduction in income risk between the two groups of households, could reflect differences in pension schemes or access to social benefits between skilled and unskilled jobs. For example, pension schemes for skilled jobs may have a better insurance component attached to them. Alternatively, University educated heads may be better informed about availability of social benefits for the members of the household. Moreover, if government policy is targeted mainly towards alleviating reductions in earnings and does not include a strong component to enhance prospects of upward mobility, it will be more effective in reducing risk associated with the lower tail than with the upper. As we have seen, for households with a University educated head, such a policy would work to reduce the increase in idiosyncratic risk. However, it is less likely to be as effective for households whose head is not University educated, since for these households changes in the upper tails are also important.

Finally, another possible explanation for the difference in the effect of government policy between the two groups of households relates to the progressivity of the tax system. In particular, the tax rate thresholds have been in effective terms about £2,000 for the lower threshold and about £30,000 for the upper threshold.[31] For households with non-University educated head, for the time period under study, about 75% of the distribution of equivalised household labour or gross income is between these two thresholds, i.e. in the basic rate tax band.[32] On the other hand, for households with University educated head, for the time period under study, only about 45% of the distribution of equivalised household labour or gross income is in the basic rate tax band. These numbers are of course indicative, as different taxes apply to different sources of income, tax bands change over time, etc.[33] They do make the point, however, that while the majority of households whose head is non-University educated are in the same tax band, households whose head is University educated span two tax bands.

This difference is important because income shocks for households with a

more pronounced for households whose head does not hold a University degree.

[31] The effective thresholds noted here are of course approximations of a much more complicated reality (see e.g. Adam *et al.* (2010)). The definition of the tax base, tax-free income, taxes per source of income, etc, has changed over the years and providing a single effective threshold for the different tax rates to apply is not straightforward. Since household income measures are expressed in 2012 prices, the thresholds reported here are closer to those at the end of the period 1991-2008.

[32] This is obtained by considering all households for all time periods. Similar estimates are obtained by considering the percentage for each time period and averaging over the time periods.

[33] For both groups, and given the sample selection criteria we have used, the percentage of households below the lower threshold is very small, less than 1%.

non-University educated head typically imply movements within the same tax band, while for households with a University educated head, income shocks often imply movements between tax bands.[34] Therefore, for households with University educated heads, big reductions in income are more likely to imply a change in the relative effective tax liability, thus reducing the impact of negative income shocks in net income terms (and vice versa for increases in income). Hence, tax progressivity and the tax bands in place work to smooth the effect of income shocks more for households with University educated heads as opposed to those with non-University educated heads.

5 Conclusions and Discussion

This paper examined the relationship between idiosyncratic earnings, employment and wage risk and fluctuations at the aggregate level for these quantities in Great Britain. We used panel data from the British Household Panel Survey (BHPS) for 1991-2008 and from the BHPS sub-sample of Understanding Society for 2010-2014. We measured idiosyncratic risk by the relevant moments of the distribution of earnings, employment and wage shocks across individuals, which we approximated by calculating the growth rate of residual earnings, employment and wage for each individual between consecutive periods. We also examined household income risk (total earnings, gross income and net income) working as above. We related these moments to changes in aggregate earnings, employment and wages.

We establish evidence of asymmetries in risk in earnings, employment and wages in the form of changes in the tails and in the skewness of the distribution between periods of expansion and contraction of the aggregate states. In particular, we found that downside risk is higher when the aggregate state that applies to the labour market quantity worsens. The increase in risk in earnings and employment is mainly driven by a significant increase in the probability of very negative shocks (a thickening of the left tail), for both University and non-University educated workers, with an additional decrease in the probability of positive earnings shocks for non-University educated workers. On the other hand, wage risk affects mainly non-University educated workers.

These results are broadly consistent with a series of recent studies focusing on asymmetric earnings and wage risk over the business cycle in Germany, Sweden and the US (see e.g. Guvenen *et al.* (2014), Busch *et al.* (2016) and

[34] Note in Appendix C, Figure C.3, that the 10th percentile of equivalised income shock implies about a 25% reduction in income and the 90th percentile shock implies an increase of about 25% in income. These magnitudes are very similar for both groups of households.

Busch and Ludwig (2016)). However, compared with these studies, our findings for Great Britain differ in a number ways. First, we find that asymmetry in earnings risk takes the form of changes in the left tail, implying that the increase in risk is due to losing substantial income, and not about reduced chances of higher income. Second, employment and wage risk affect workers in distinct skill groups differently. Third, labour income risk can increase even when the aggregate economy is growing. Therefore, the findings in this paper indicate a further asymmetry in labour income risk, i.e. within periods of GDP expansion. In turn, this suggests that increases in idiosyncratic labour income risk should be a concern for policymakers not only in economic downturns, but also in periods of positive aggregate economic performance.

We established that employment risk, broadly defined to include the probability of being unemployed for a long period, increases in downturns (consistent with e.g. Blass-Hoffmann and Malacrino (2016)). However, we also found that risk in returns-to-labour matters. More specifically, when we look at the sources of earnings risk, in particular into the time input and the return input to earnings, we found that it is predominantly the return to labour input component that drives the behaviour of earnings risk. Hence, public insurance is not only an issue of providing unemployment benefits, or improving prospects for employment in downturns, but also about improving the resilience of wage growth prospects in response to changes in mean wages. This is especially relevant for unskilled (non-University educated) workers, whose prospects for wage growth we found to be significantly dependent on mean wage growth. Additionally, it is important for households whose head does not have a University degree, for whom prospects of income rises also depend on mean earnings growth.[35]

Obviously, policy interventions to improve prospects of upward mobility in periods of labour market contractions are not easy to design, as they require a long-term intervention to improve the skill set of workers, as opposed to short-term interventions to alleviate income reductions. Our results imply that public insurance mechanisms reduce, but do not eliminate the increase in household income risk for households whose head is not University educated, when mean earnings are reduced. Moreover, this group of households does not seem effective in using income from assets and private transfers to smooth the big negative earnings shocks. Overall, our results suggest that there is incomplete insurance from the increase in earnings risk when labour market conditions worsen.

[35] More generally, the changes in the upper tail have been found to be significant in the majority of the results we obtained when analysing the non-University educated sample for different measures of income risk.

We further found that the variance of the idiosyncratic shocks to wages increases with negative shocks at the aggregate level (mean wages), in addition to the increase in asymmetry. The variance result supports theoretical analysis which assumes that the variance of the idiosyncratic earnings shock rises when the aggregate state worsens.[36] As discussed in the Introduction, theoretical studies that incorporate asymmetric earnings variance and/or skewness have been shown to better explain macroeconomic outcomes.

Given that our time period covers up to 23 years, we looked at annual growth rates of income measures (and of their unobserved component) to approximate idiosyncratic shocks. These growth rates include both permanent and transitory shocks, which have different implications for economic behaviour. For instance, economic theory suggests that individuals smooth transitory shocks and their consumption is mainly affected by permanent shocks. This should be kept in mind when evaluating the findings in this paper. However, it should also be noted that smoothing of transitory shocks is possible when individuals have access to perfect financial markets and that, in their absence, consumption smoothing/insurance from shocks becomes more difficult, especially for big negative income shocks. Therefore, to the extent that asset and insurance markets are imperfect, the increase in earnings risk we find likely implies that transitory earnings shocks have similar effects on households as permanent ones.

6 Appendix A: Data

6.1 Datasets

The main datasets used in this paper include the British Household Panel Survey (BHPS) and the BHPS sub-sample of the subsequent Understanding Society Survey. The BHPS is a comprehensive longitudinal study for the U.K. running from 1991 to 2008. As a panel data survey, the BHPS tracks individuals across households over time. In the first wave, the BHPS achieved a sample size of around 5000 households (10,000 adult interviews) or a 65% response rate. After the first wave, due to sample attrition, the sample size shrank slightly. For example, in 2000 it achieved around 4200 complete interviews or a 75% response rate (see Taylor *et al.* 2010).

Since the start of BHPS in 1991, a number of additional sub-samples have been added to the survey. For example, the European Community Household Panel Survey (ECHP) sub-sample started in 1997. It was added mainly to

[36] Note that this refers to models which assume that labour supply is exogenous. Thus, earnings risk is effectively labour productivity risk.

include respondents from Northern Ireland and a low-income sample from the U.K. However, to maintain the longest possible time-series dimension in our analysis we only use data starting in 1991. Thus, our focus on Great Britain. Finally, following Blundell and Etheridge (2010), we also make use of an auxiliary dataset called "Derived Current and Annual Net Household Income Variables" compiled by Bardasi *et al.* (2012).

In 2008 the respondents in the BHPS were asked if they would agree to continue being interviewed for a new panel data survey called Understanding Society. Those agreeing were interviewed again starting in 2010. Thus, the reason for the missing year (2009) discussed in the main text. For the most part, the questionnaire was the same and most of the derived variables are available in the same format.

The BHPS and the Understanding Society (BHPS sub-sample) contain detailed information on key magnitudes of interest for this paper. In particular, earnings, hours worked and other income. Compared to other U.K. panel datasets for earnings, e.g. the New Earnings Survey (NES) for the period 1975-2002 and the Annual Survey of Hours and Earnings (ASHE), for the period 1997-2015. BHPS is much smaller in the cross-sectional dimension.

On the plus side, in contrast to the NES and ASHE, the BHPS has information on both individual and household characteristics. Therefore, it allows the examination of compositional effects (i.e. differences between individuals and households) and thus issues relating to household insurance mechanisms. Moreover, BHPS provides important human capital variables such as educational attainment. Another, important advantage of the BHPS relates to hourly pay. As noted by Stewart and Swaffield (2002), the BHPS does not suffer from the potentially serious sample selection bias that exists in the NES. In particular, workers earning below the pay-as-you-earn tax threshold are under-represented in the NES sample. Furthermore, NES and ASHE only cover employees and therefore exclude the self-employed and the unemployed.

6.2 Demographic and socioeconomic variables

1. **Head and relationship to head**: For each individual in the sample, BHPS reports the relationship to the head of household in any given wave. In our analysis we focus on households whose head is married. Following Blundell and Etheridge (2010), the head of the household is defined as the oldest married (or living in partnership) male within the household.

2. **Education level**: BHPS and Understanding Society both include in-

formation on educational attainment. To obtain consistent variables for education across the two datasets we pooled the individuals into five groups: (i) degree; (ii) other higher/diploma/teaching/nursing; (iii) A-levels/AS level/Highers; (iv) GCSE/O level; (v) other qualification/no qualifications. For the BHPS we have used the variable wQFEDHI (where the prefix w denotes wave) and for Understanding Society the variable wHIQUAL_DV. The strategy we follow is to allocate the individuals in the Understanding Society survey to the same educational group to which they belonged in the years before 2009. Given that the analysis is on individuals above the age of 25, this is a reasonable starting point. However, there are cases where some individuals gained a higher level of education after this age. In these instances their educational attainment was modified accordingly. To examine potential heterogeneity of earnings and wage risk in the main text, the sample is split into degree holders and non-degree holders. The former are the individuals who belong to group (i), while the latter belong to groups (ii)-(v). Following Blundell and Etheridge (2010), to create the dummy variables for the regression in equation (4), we use the following education categories: (a) high education includes those with a higher or first degree, city and guilds certificates, and other higher diplomas, i.e. groups (i) and (ii) above; (b) intermediate education includes those with A-levels or equivalent, i.e. group (iii) above; (b) and 'low education' is the remainder, i.e. groups (iv) and (v) above.

6.3 Income and hours variables

1. **Individual annual earnings**:[37] measures annual labour income in the reference year from September in the year prior to the interview until September in the year which interviewing begins and is denoted wFIYRL. If the individual is self-employed we multiply their earnings by 2/3 to reflect an average non-labour income share of 1/3 (see, e.g. Heathcote *et al.* (2010)). When monetary amounts are missing, BHPS uses a regression-based imputation method known as 'predictive mean matching' for a number of primary variables from which some other income-related variables are derived. Following the literature (e.g. Blundell and Etheridge (2010)) we do not use the observations with imputed values in our analysis.

2. **Annual hours**: is comprised of the usual weekly hours worked, wJBHRS, the usual weekly hours worked by the self-employed, wJBHRS, and the

[37] All monetary values are expressed in 2012 prices.

number of weeks an individual worked, wNJBWKS. Annual hours is wNJBWKS multiplied by wJBHRS if the individual is employee, or wJSHRS if the individual is self-employed.

3. **Hourly returns**: are equal to individual annual earnings, wFIYRL, divided by annual hours calculated in 2.

4. **Hourly wages**: are equal to usual weekly labour earnings divided by usual weekly hours worked. Note the self-employed are excluded. To derive hourly wages, monthly earnings or salary payments before tax and other deductions in the current main job for employees, wPAYGU, are multiplied by 12/52. These are then divided by usual weekly hours, wJBHRS, to obtain the hourly wage.

5. **Minimum wage**: is the lowest wage per hour a worker is entitled to in the U.K. The minimum wage was introduced in the U.K. in 1999 and we have the official level only after this year. Thus, to have an approximation of the minimum wage for the years before 1999, we employ a linear projection of the minimum wage in nominal terms.

6. **Household total earnings**: are defined as the sum of individual annual earnings (see the definition above) within the household. Imputed values are included only if they refer to a respondent who is not the head of the household.

7. **Household gross income**: is obtained from the Derived Current and Annual Net Household Income Variables dataset (Bardasi *et al.* 2012). Gross income is equal to household annual labour earnings, wHHYRLG, plus annual investment income, wHHYRI, plus annual private transfers income, wHHYRT.

8. **Household earnings plus benefits**: is equal to household total earnings, plus social benefits, wHHYRB, plus annual private transfers income, wHHYRT. The last two are obtained from the Derived Current and Annual Net Household Income Variables dataset (Bardasi *et al.* 2012).

9. **Household net income**: is from the Derived Current and Annual Net Household Income Variables dataset (Bardasi *et al.* 2012) and is denoted, wHHYNETI. It is defined as household annual labour income less pension contributions, national insurance and payroll taxes, plus annual investment, plus pension income, plus annual private transfers income and annual social benefits income.

6.4 Sample selection

For all of the measures discussed below, to employ a consistent sample throughout, we use the original BHPS sample excluding the observations from the boost samples after 1997. For each measure, to construct the cross-sectional sample in each year we make use of the sampling weights provided by BHPS. Hence, sampling weights inform the required percentages for sample trimming and calculating mean values per year.

6.4.1 Individual annual earnings

In each year, we retain male individuals in the main working age of 25-60 who report positive annual earnings and their educational attainment. Following (Busch *et al.* 2016) we exclude the observations belonging to the top 1% of the earnings distribution in each year. As in Busch *et al.* (2016), Guvenen *et al.* (2014), to ensure a strong attachment to the labour marker in any year, we include individuals who report an annual income greater than half the minimum legal hourly wage times 520 hours, implying at least a few months of work during the year.

Table A.1: Individual annual earnings

selection step	all	males	females
whole sample	236,902	109,396	127,506
drop proxy & non-full interviews	227,391	103,616	123,775
original sample	149,809	69,410	80,399
no educational info	146,974	67,913	79,061
drop if in military	146,836	67,782	79,054
drop if region missing	146,751	67,743	79,008
age $\geq$25, $\leq$60	92,432	43,586	48,846
earnings>0	64,882	32,330	32,552
top1%	64,292	32,043	32,249
below threshold	62,996	31,822	31,174
one year changes	49,543	25,131	24,412
ave. N obs	3,500	1,768	1,732
ave. N obs of one year changes	2,914	1,478	1,436
ave. N obs Uni of one year changes	525	287	238
ave. N obs Non-Uni of one year changes	2,389	1,191	1,198

6.4.2 Individual annual hours worked

We drop individuals who have been inactive in the labour market (e.g. full time students, long-term sick/disabled, those on maternity leave) for more than 13 weeks. We also drop those individuals whose responses imply that they worked for more than 84 hours a week. Finally, we keep individuals with positive hours of employment.

Table A.2: Individual annual hours worked

selection step	all	males	females
whole sample	236,902	109,396	127,506
drop proxy & non-full interviews	227,391	103,616	123,775
original sample	149,809	69,410	80,399
no educational info	146,974	67,913	79,061
drop if in military	146,836	67,782	79,054
drop if region missing	146,751	67,743	79,008
age $\geq$25, $\leq$60	92,432	43,586	48,846
hours non missing	71,791	36,938	34,853
non inactive	70,943	36,753	34,190
above 84 hours per week	70,683	36,551	34,132
positive hours worked	70557	36482	34075
one year changes	57,525	29,974	27,551
ave. N obs	3,728	1933	1,795
ave. N obs of one year changes	3,384	1,763	1,621
ave. N obs Uni of one year changes	593	321	272
ave. N obs Non-Uni of one year changes	2,791	1,443	1348

6.4.3 Individual hourly wages

We use the original BHPS sample, excluding the observations from the boost samples, and the Understanding Society, BHPS sub-sample. From the latter, we retain only the respondents that they were in the original sample of the BHPS. We restrict the sample to employed males with positive hourly wages. As discussed in the main text, we also trim the top and bottom 0.5% of the wage distribution in each year. At the lower end, this effectively discards those individuals with less than about half the minimum wage.

Table A.3: Hourly wages

selection step	all	males	females
whole sample	529,580	243,994	285,586
drop proxy & non-full interviews	497,954	223,375	274,579
original sample	175,281	80,848	94,433
drop if in military	175,130	80,707	94,423
no educational info	172,123	79,144	92,979
drop if region missing	172,013	79,095	92,918
age $\geq$25, $\leq$60	108,334	50,817	57,517
wages>0	69,756	33,312	36,444
below 99.5% and above 0.5%	69,116	33,001	36,115
one year changes	53,214	25,576	27,638
ave. N obs	2,927	1,397	1,530
ave. N obs of one year changes	2,534	1,218	1,316
ave. N obs Uni of one year changes	498	253	241
ave. N obs Non-Uni of one year changes	2,031	965	1,065

6.4.4 Household income

We construct households from 1991-2008 by starting with the allocation of individuals to households from BHPS and retain households with a spouse/partner relationship. The household heads must be between 25-60 years of age, report non-zero labour income and their individual earnings should be reported and not imputed. Households comprised of a single member or those that involve cohabiting but not family-related members are discarded. Moreover, the head must not be in the military and must not have missing values for region and educational attainment. For the remaining households, we obtain the household annual labour income from the "Derived Current and Annual Net Household Income Variables" dataset (Bardasi *et al.* 2012) and we drop households at the top 1% of the household total earnings distribution of the corresponding year. We also discard households whose annual labour income is less than half of the product between the minimum legal hourly wage times 520 hours. Household annual gross and net income are also from the "Derived Current and Annual Net Household Income Variables" dataset (Bardasi *et al.* 2012).

Table A.4: Households and household members

selection step	households	heads	spouses
whole Sample	130,974	130,974	
drop proxy & non-full interviews	128,348	128,348	75,279
original sample	82,355	82,355	50,044
full interview of all members in household	74,602	74,602	44,904
head's educational info missing	73,739	73,739	44,469
drop if head in military	73,662	73,662	44,392
head's region missing	73,638	73,638	44,368
keep if more than 2 adults	48,912	48,912	44,152
heads' age $\geq$25, $\leq$60	35,879	35,879	32,813
head's earnings$>$ 0 & living with spouse	24,725	24,725	24,725
drop if top1% of household total earnings	24,501	24,501	24,501
household total earnings$>$threshold	24,456	24,456	24,456
one year changes	18,980	18,980	14,927
ave. N obs	1,359	1,359	1,111
ave. N obs of one year changes	1,116	1,116	878
ave. N obs Uni of one year changes	-	208	176
ave. N obs Non-Uni of one year changes	-	909	697

7 Appendix B: Growth Results

Table B.1: Moment Regressions, earnings growth

	Variance	Kelly	P90/50	P50/10	P90/10
			Males		
$\widehat{\gamma}$ coef.	0.158	4.523	1.245	-0.923	0.322
pval. $\widehat{\gamma}$	0.457	**0.014**	**0.079**	**0.064**	0.701
pval. D.W.	0.705	0.151	**0.034**	0.218	**0.032**
			University educated males		
$\widehat{\gamma}$ coef.	-0.021	5.027	1.560	-0.873	0.687
pval. $\widehat{\gamma}$	0.967	**0.051**	**0.084**	0.184	0.484
pval. D.W.	0.620	0.935	**0.020**	0.171	0.437
			Non-university educated males		
$\widehat{\gamma}$ coef.	0.220	4.269	1.169	-0.916	0.254
pval. $\widehat{\gamma}$	0.317	**0.016**	**0.089**	**0.057**	0.756
pval. D.W.	0.972	0.234	**0.061**	0.227	**0.032**
			Females		
$\widehat{\gamma}$ coef.	0.464	3.186	1.458	-0.487	0.972
pval. $\widehat{\gamma}$	**0.056**	**0.027**	**0.023**	0.304	0.210
pval. D.W.	**0.048**	0.345	0.671	0.584	**0.027**

Table B.2: Moment Regressions, sources of earnings risk

	Variance	Kelly	P90/50	P50/10	P90/10
			Earnings growth		
$\widehat{\gamma}$ coef.	0.156	3.534	1.105	-0.512	0.593
pval. $\widehat{\gamma}$	0.268	**0.023**	0.110	0.154	0.482
pval. D.W.	0.616	0.242	**0.038**	0.150	**0.015**
			Annual hours growth		
$\widehat{\gamma}$ coef.	-0.143	-0.331	0.154	0.144	0.298
pval. $\widehat{\gamma}$	0.289	0.674	0.268	0.211	**0.058**
pval. D.W.	0.176	0.171	0.499	0.582	0.378
			Hourly return growth		
$\widehat{\gamma}$ coef.	0.056	3.168	0.922	-0.587	0.335
pval. $\widehat{\gamma}$	0.582	**0.009**	0.132	**0.067**	0.654
pval. D.W.	0.327	0.690	0.127	0.203	**0.037**

Table B.3: Moment Regressions, hours growth

	Variance	Kelly	P90/50	P50/10	P90/10
			Males		
$\widehat{\gamma}$ coef.	0.723	5.648	0.980	-0.632	0.348
pval. $\widehat{\gamma}$	**0.048**	**0.022**	**0.077**	**0.067**	0.541
pval. D.W.	0.669	0.577	0.736	0.532	0.958
			University educated males		
$\widehat{\gamma}$ coef.	-1.793	-3.729	-3.522	-2.310	-5.832
pval. $\widehat{\gamma}$	0.169	0.577	**0.010**	**0.091**	**0.001**
pval. D.W.	0.513	0.367	0.494	0.323	0.501
			Non-university educated males		
$\widehat{\gamma}$ coef.	1.141	7.705	1.387	-0.762	0.624
pval. $\widehat{\gamma}$	**0.038**	**0.007**	**0.043**	**0.067**	0.425
pval. D.W.	0.511	0.423	0.840	0.150	0.956
			Females		
$\widehat{\gamma}$ coef.	0.442	4.927	2.379	-0.494	1.884
pval. $\widehat{\gamma}$	0.434	**0.082**	**0.045**	0.520	0.135
pval. D.W.	0.808	0.482	0.671	0.342	0.787

Table B.4: Moment Regressions, wage growth

	Variance	Kelly	P90/50	P50/10	P90/10
			Males		
$\widehat{\gamma}$ coef.	-0.097	1.582	0.454	-0.271	0.183
pval. $\widehat{\gamma}$	**0.054**	**0.016**	**0.033**	0.102	0.454
pval. D.W.	0.984	0.399	0.520	0.566	0.659
			University educated males		
$\widehat{\gamma}$ coef.	-0.082	0.318	0.143	-0.021	0.121
pval. $\widehat{\gamma}$	0.460	0.840	0.734	0.941	0.680
pval. D.W.	0.287	**0.029**	0.136	**0.008**	0.333
			Non-university educated males		
$\widehat{\gamma}$ coef.	-0.106	2.362	0.652	-0.446	0.206
pval. $\widehat{\gamma}$	**0.121**	**0.001**	**0.004**	**0.033**	0.472
pval. D.W.	0.738	0.359	0.658	0.361	0.938
			Females		
$\widehat{\gamma}$ coef.	0.137	0.225	0.291	0.156	0.447
pval. $\widehat{\gamma}$	0.135	0.700	**0.066**	0.305	**0.012**
pval. D.W.	0.804	**0.077**	0.737	0.216	0.211

Table B.5: Moment Regressions, household earnings/income growth

	Variance	Kelly	P90/50	P50/10	P90/10
			Total earnings		
$\widehat{\gamma}$ coef.	0.022	2.769	0.574	-0.835	-0.261
pval. $\widehat{\gamma}$	0.883	**0.001**	**0.089**	**0.001**	0.523
pval. D.W.	0.820	**0.082**	**0.037**	0.688	0.131
			Head earnings		
$\widehat{\gamma}$ coef.	-0.030	3.952	1.060	-0.816	0.244
pval. $\widehat{\gamma}$	0.936	**0.025**	0.175	**0.049**	0.790
pval. D.W.	0.891	**0.065**	**0.050**	0.226	**0.071**
			Spouse earnings		
$\widehat{\gamma}$ coef.	3.195	3.414	2.296	-0.529	1.767
pval. $\widehat{\gamma}$	**0.022**	**0.048**	**0.004**	0.517	**0.063**
pval. D.W.	0.401	0.291	0.604	0.424	0.261
			Gross income		
$\widehat{\gamma}$ coef.	0.043	2.330	0.544	-0.644	-0.101
pval. $\widehat{\gamma}$	0.768	**0.010**	0.116	**0.009**	0.791
pval. D.W.	0.952	**0.045**	**0.018**	0.607	0.133
			Earnings plus benefits		
$\widehat{\gamma}$ coef.	0.054	2.158	0.446	-0.570	-0.124
pval. $\widehat{\gamma}$	0.525	**0.003**	0.113	**0.002**	0.714
pval. D.W.	0.673	0.431	0.172	0.978	0.202
			Net income		
$\widehat{\gamma}$ coef.	0.006	1.468	0.286	-0.373	-0.087
pval. $\widehat{\gamma}$	0.915	**0.010**	0.208	**0.034**	0.782
pval. D.W.	0.599	0.862	0.151	0.809	0.203

Table B.6: Moment Regressions,
household income growth, by education

	Variance	Kelly	P90/50	P50/10	P90/10
	Total earnings university educated				
$\widehat{\gamma}$ coef.	-0.311	2.762	0.398	-0.952	-0.553
pval. $\widehat{\gamma}$	0.452	**0.043**	0.490	**0.047**	0.507
pval. D.W.	0.375	0.101	0.286	0.668	0.867
	Gross income university educated				
$\widehat{\gamma}$ coef.	-0.321	2.141	0.184	-0.932	-0.747
pval. $\widehat{\gamma}$	0.328	0.112	0.747	**0.011**	0.271
pval. D.W.	0.284	0.247	0.266	0.340	0.288
	Earnings plus benefits university educated				
$\widehat{\gamma}$ coef.	-0.304	2.585	0.355	-0.869	-0.514
pval. $\widehat{\gamma}$	0.289	**0.039**	0.506	**0.023**	0.482
pval. D.W.	0.334	0.327	0.324	0.931	0.504
	Net income university educated				
$\widehat{\gamma}$ coef.	-0.336	1.828	0.221	-0.642	-0.421
pval. $\widehat{\gamma}$	**0.057**	0.103	0.619	**0.040**	0.461
pval. D.W.	0.208	0.865	0.457	0.791	0.318
	Total earnings non-university educated				
$\widehat{\gamma}$ coef.	0.120	2.590	0.530	-0.810	-0.279
pval. $\widehat{\gamma}$	0.352	**0.002**	**0.088**	**0.002**	0.451
pval. D.W.	0.754	0.391	**0.088**	0.748	0.133
	Gross income non-university educated				
$\widehat{\gamma}$ coef.	0.141	2.128	0.550	-0.554	-0.004
pval. $\widehat{\gamma}$	0.283	**0.014**	0.124	**0.020**	0.992
pval. D.W.	0.581	0.207	**0.036**	0.786	**0.093**
	Earnings plus benefits non-university educated				
$\widehat{\gamma}$ coef.	0.148	2.159	0.491	-0.548	-0.057
pval. $\widehat{\gamma}$	0.169	**0.002**	**0.081**	**0.001**	0.862
pval. D.W.	0.992	0.818	0.493	0.782	0.326
	Net income non-university educated				
$\widehat{\gamma}$ coef.	0.088	1.572	0.383	-0.320	0.063
pval. $\widehat{\gamma}$	0.185	**0.008**	0.110	**0.045**	0.837
pval. D.W.	0.387	0.725	**0.095**	0.575	**0.125**

8 Appendix C: Additional Results

In Figures C.1-C.3 we present additional results for individual and household labour income risk, which have been discussed in the main body of the text.

[Figures $C.1 - C.3$ here]

In Table C.1, we summarise the coefficient estimates, $\widehat{\gamma}$, in regressions for residual hours when ΔY_t is measured by GDP growth. We consider the four samples employed elsewhere, namely males, males with a University degree, males without a University degree, and females. The results reported in Table C.1 are similar to those obtained in Table 3, where ΔY_t is measured by growth in mean hours worked. In summary, and as can be seen in Table C.1, the variance of hours shocks for non-University educated males, as well as for the whole sample of males is pro-cyclical, while for University educated males it is counter-cyclical. Moreover, left-skewness is counter-cyclical for non-University educated males, while for University educated males changes in the both the upper and lower tale are counter-cyclical, although only the latter coefficient is significant in Table C.1. For females and University educated males, changes in the upper tail are pro-cyclical.

Table C.1: Moment Regressions, residual hours growth on UK GDP growth

	Variance	Kelly	P90/50	P50/10	P90/10
			Males		
$\widehat{\gamma}$ coef.	0.428	2.359	0.640	-0.068	0.573
pval. $\widehat{\gamma}$	**0.076**	0.219	**0.049**	0.837	0.117
pval. D.W.	0.810	0.537	0.101	0.744	0.388
			University educated males		
$\widehat{\gamma}$ coef.	-1.951	0.299	-1.185	-1.191	-2.376
pval. $\widehat{\gamma}$	**0.011**	0.918	0.111	**0.049**	**0.015**
pval. D.W.	0.377	0.543	0.909	0.880	0.448
			Non-university educated males		
$\widehat{\gamma}$ coef.	0.810	3.477	1.090	0.079	1.169
pval. $\widehat{\gamma}$	**0.021**	**0.069**	**0.002**	0.796	**0.002**
pval. D.W.	0.880	0.398	0.285	0.646	0.277
			Females		
$\widehat{\gamma}$ coef.	0.291	1.997	1.332	0.054	1.386
pval. $\widehat{\gamma}$	0.415	0.265	**0.096**	0.904	**0.099**
pval. D.W.	0.951	0.999	0.938	0.418	0.775

Finally, in Table C.2, we summarise the coefficient estimates, $\widehat{\gamma}$, for ΔY_t being measured by GDP growth in regressions for $m(\Delta y_{i,t})$.

Table C.2: Moment Regressions, hours growth on UK GDP growth

	Variance	Kelly	P90/50	P50/10	P90/10
			Males		
$\widehat{\gamma}$ coef.	0.429	3.229	0.853	-0.086	0.767
pval. $\widehat{\gamma}$	**0.075**	**0.048**	**0.012**	0.717	**0.024**
pval. D.W.	0.795	0.301	0.261	0.523	0.880
			University educated males		
$\widehat{\gamma}$ coef.	-1.945	2.609	-1.415	-2.153	-3.568
pval. $\widehat{\gamma}$	**0.013**	0.547	0.141	**0.009**	**0.003**
pval. D.W.	0.342	0.488	0.592	0.520	0.751
			Non-university educated males		
$\widehat{\gamma}$ coef.	0.806	3.787	1.161	0.081	1.242
pval. $\widehat{\gamma}$	**0.021**	**0.056**	**0.005**	0.777	**0.006**
pval. D.W.	0.868	0.322	0.586	0.263	0.867
			Females		
$\widehat{\gamma}$ coef.	0.319	1.485	1.377	0.254	1.631
pval. $\widehat{\gamma}$	0.383	0.439	**0.078**	0.612	**0.039**
pval. D.W.	0.993	0.685	0.680	0.559	0.834

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Figure 1: Aggregate Shocks and Inequality

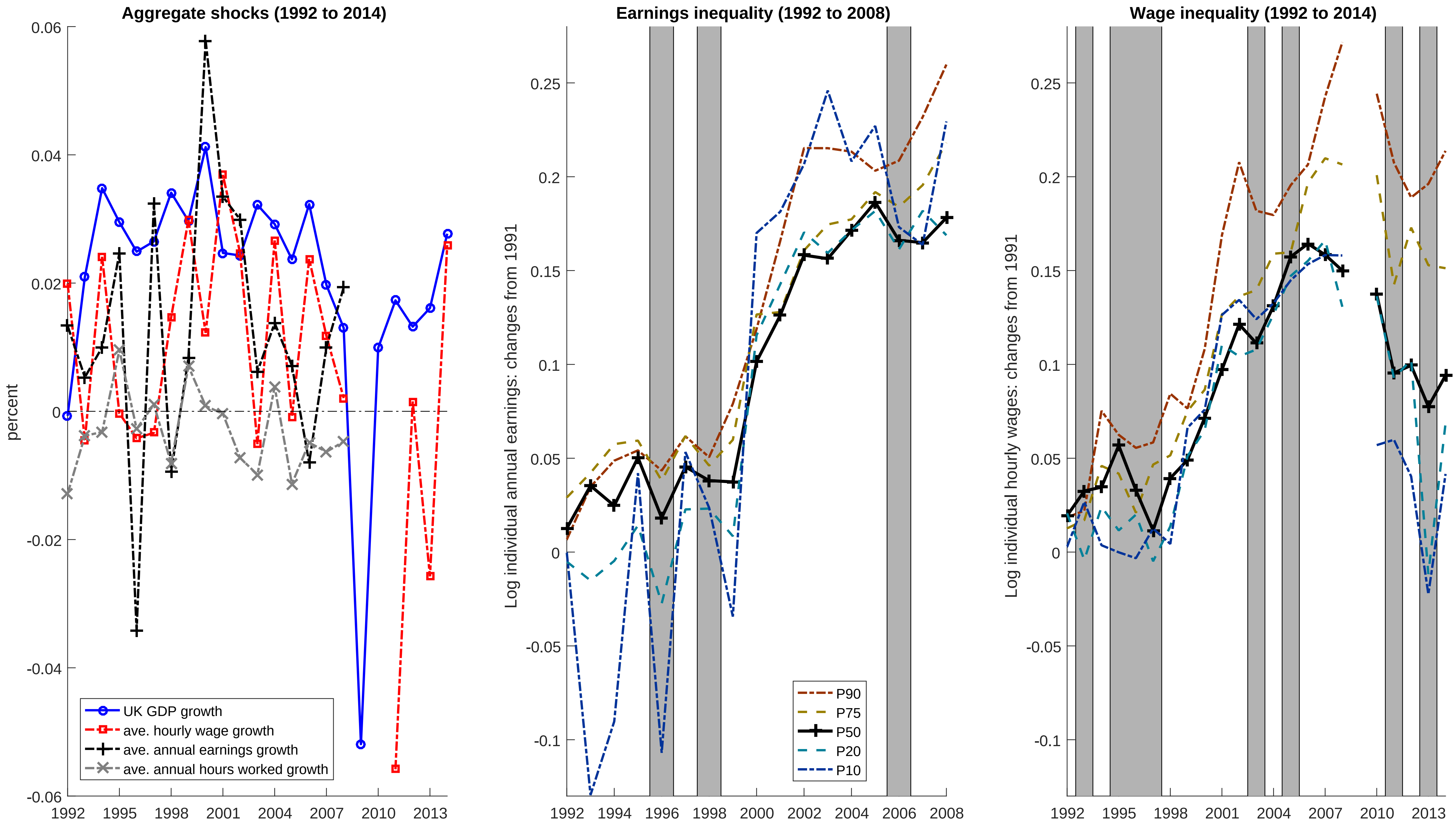


Figure 2: Skewness and Variance of Earnings Growth and Residual Earnings Growth

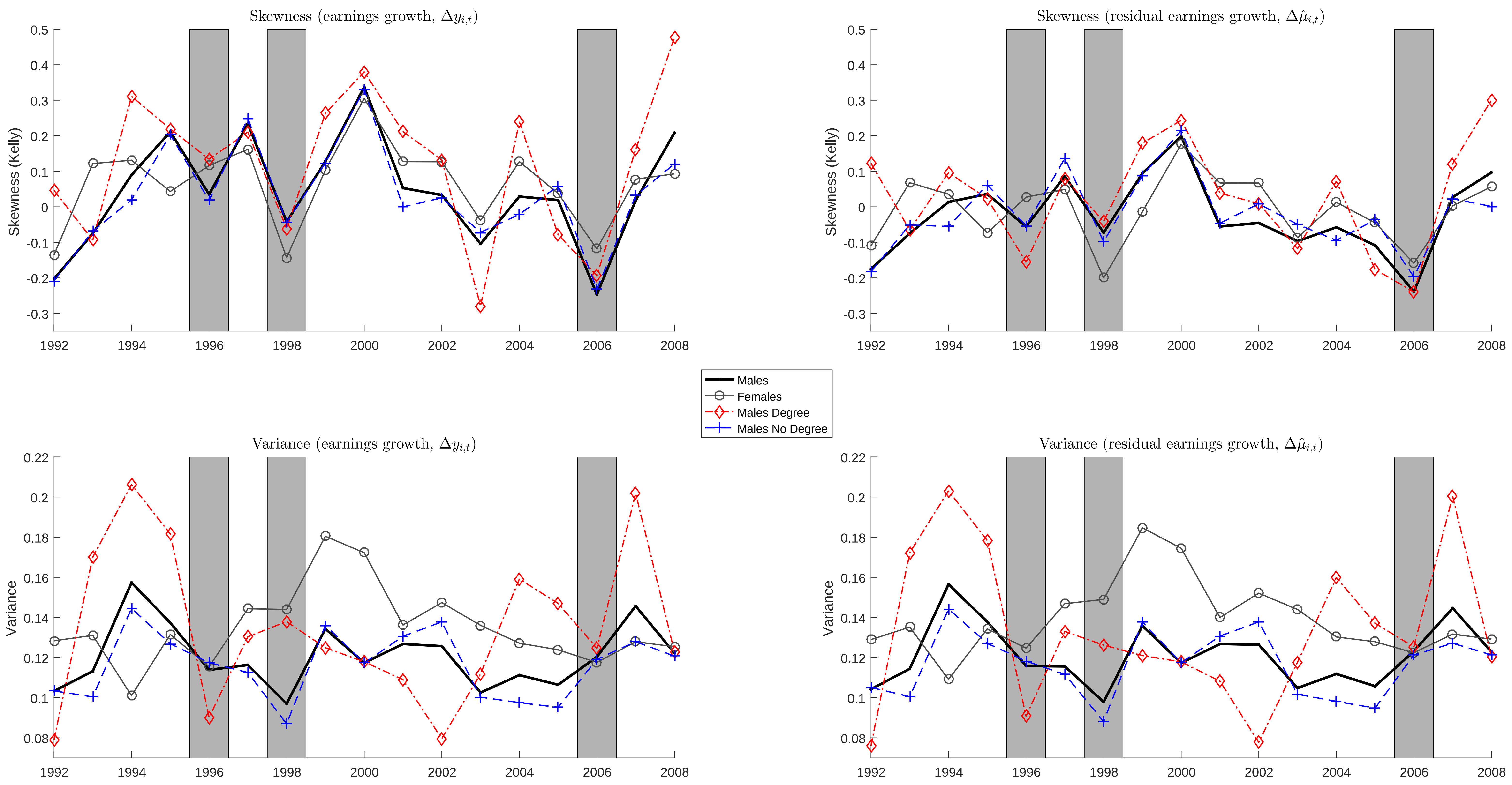


Figure 3: Skewness and Variance of Employment Growth and Residual Employment Growth

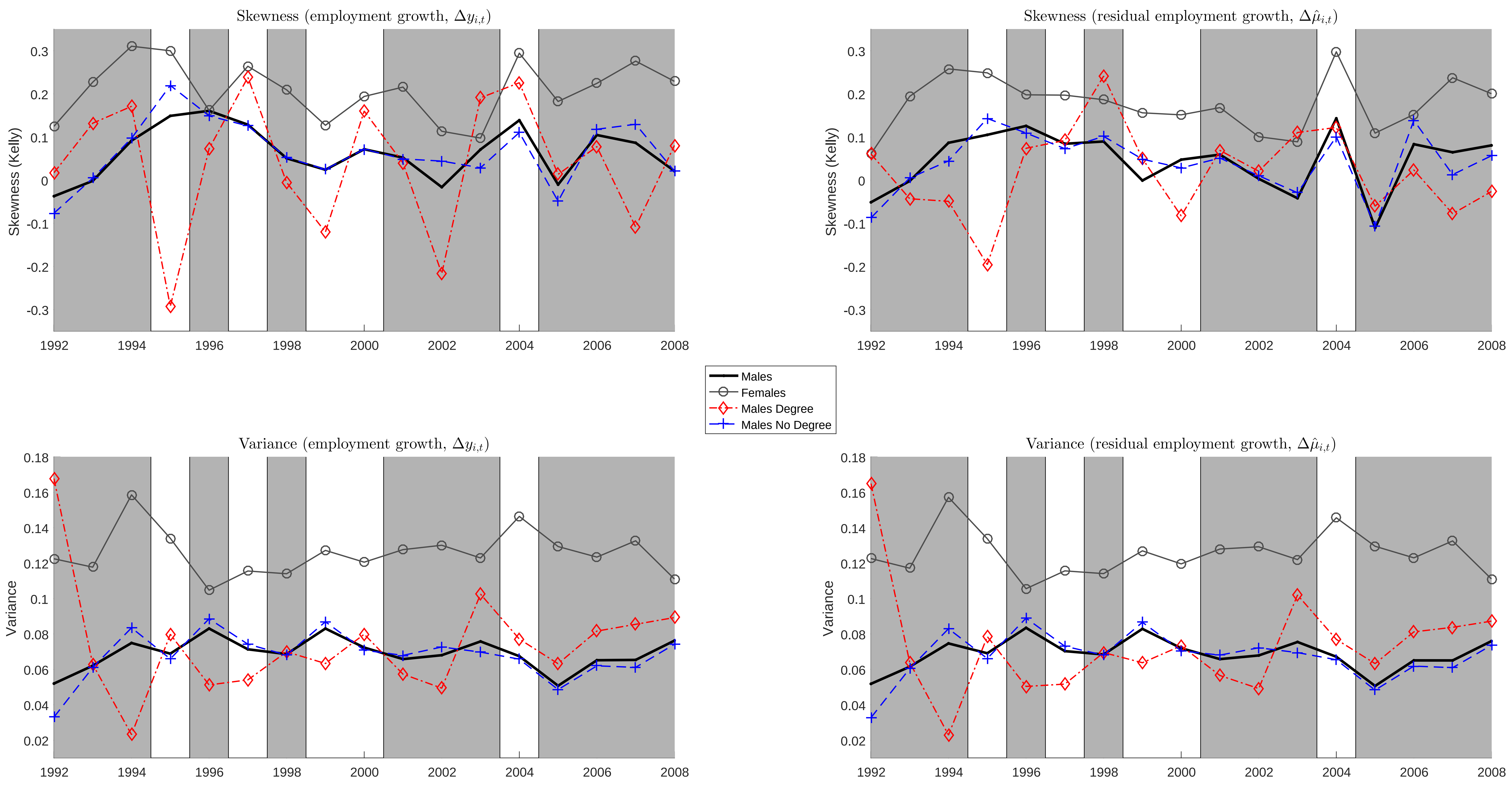


Figure 4: Skewness and Variance of Wage Growth and Residual Wage Growth

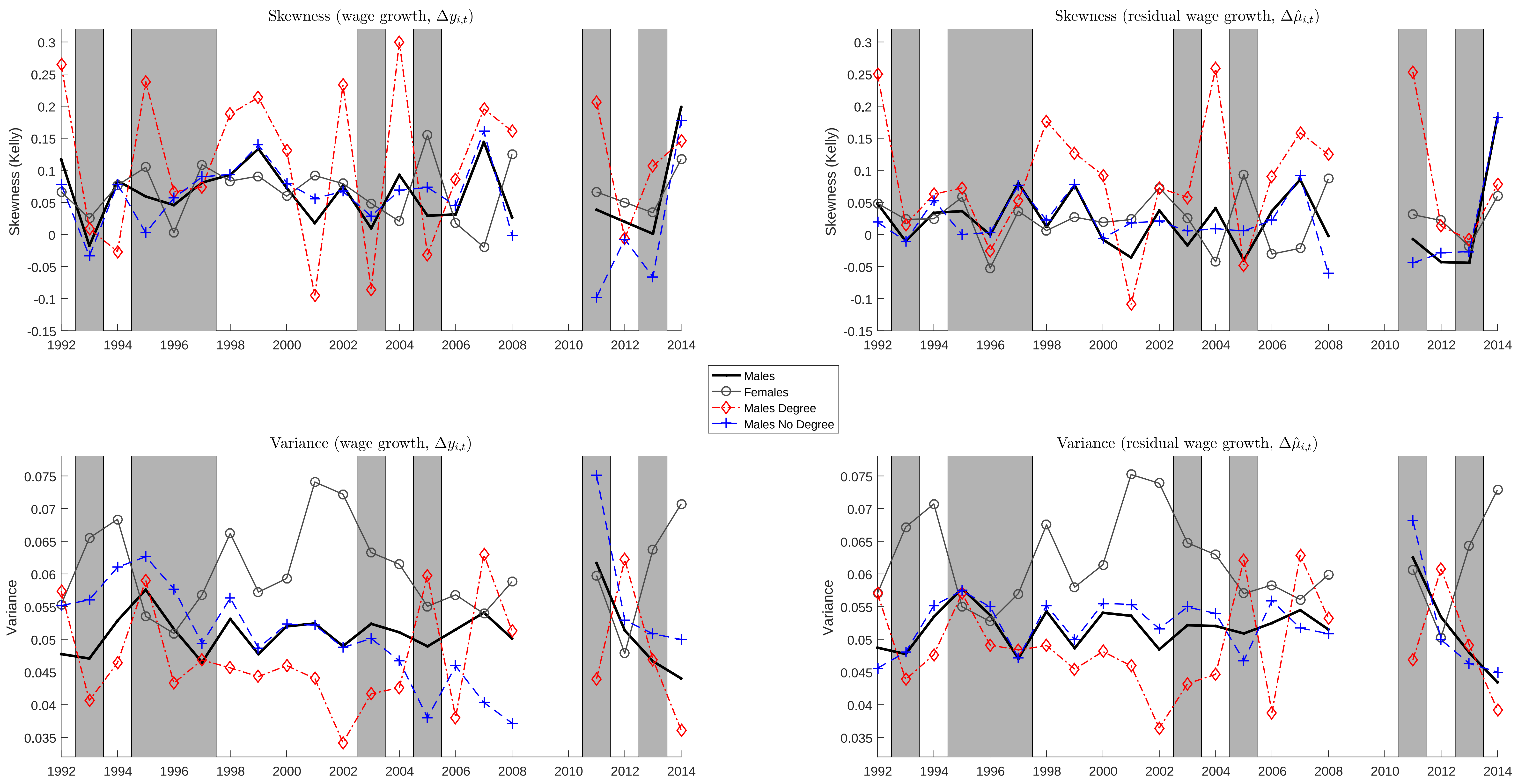
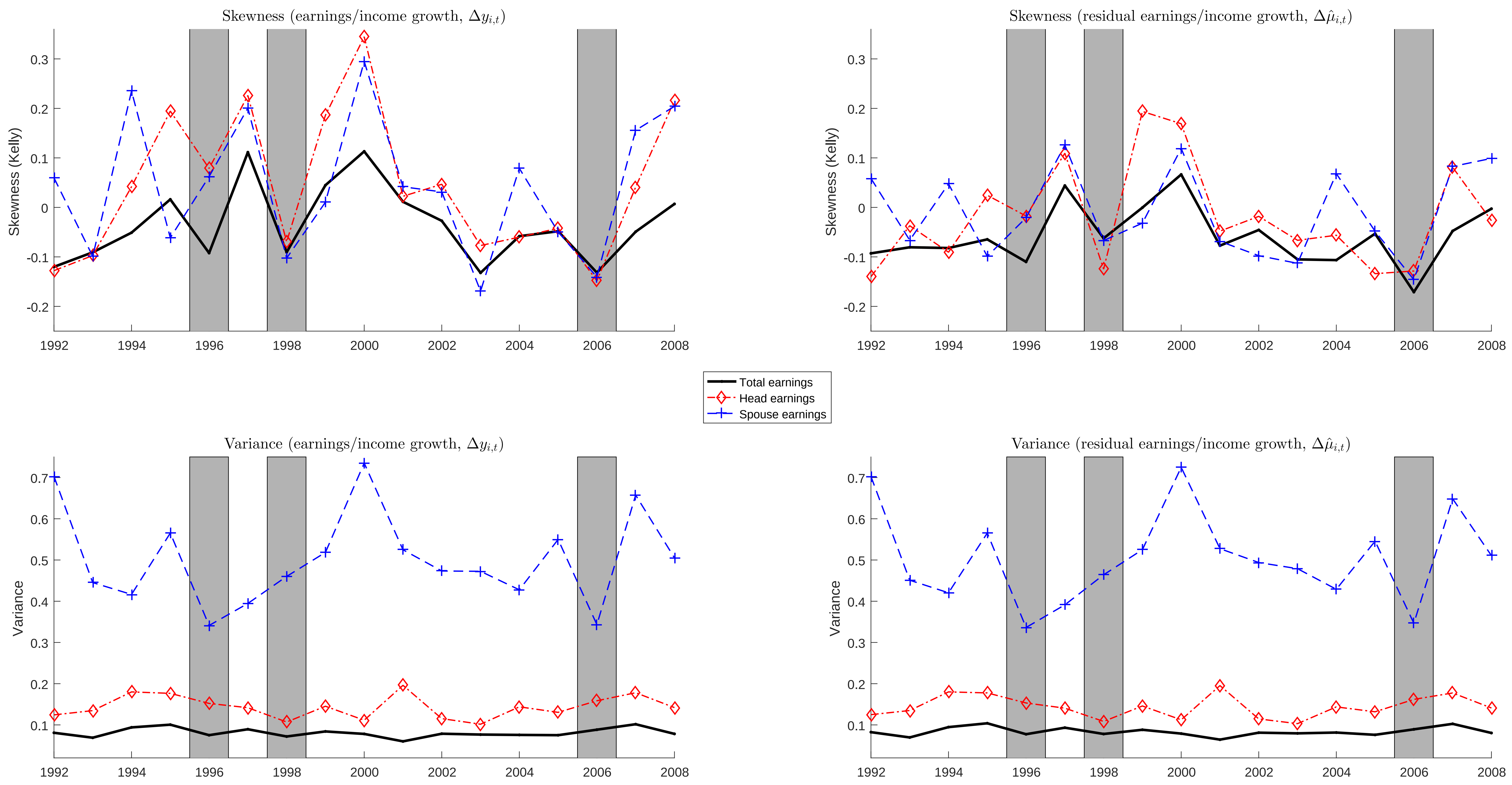
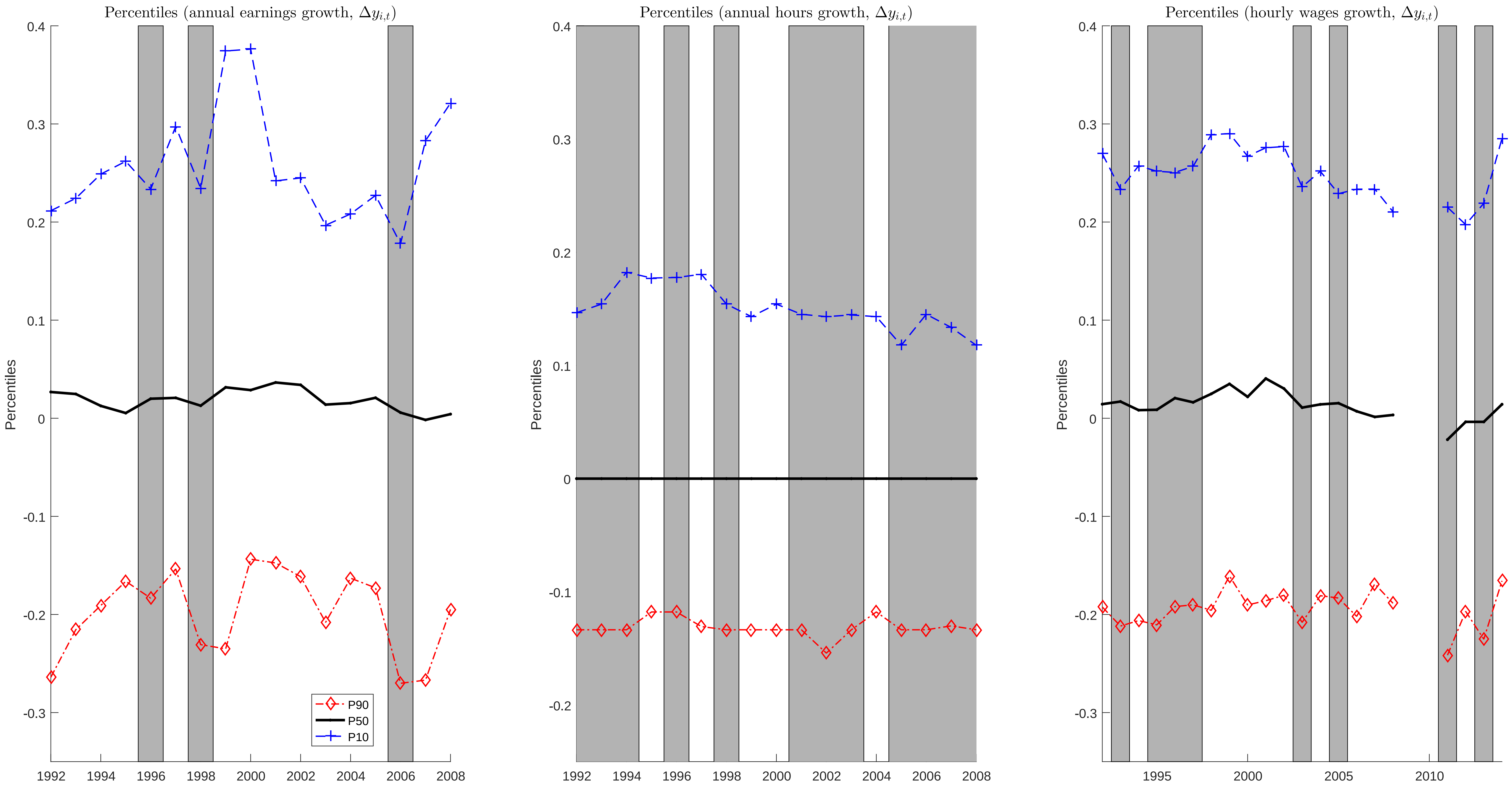


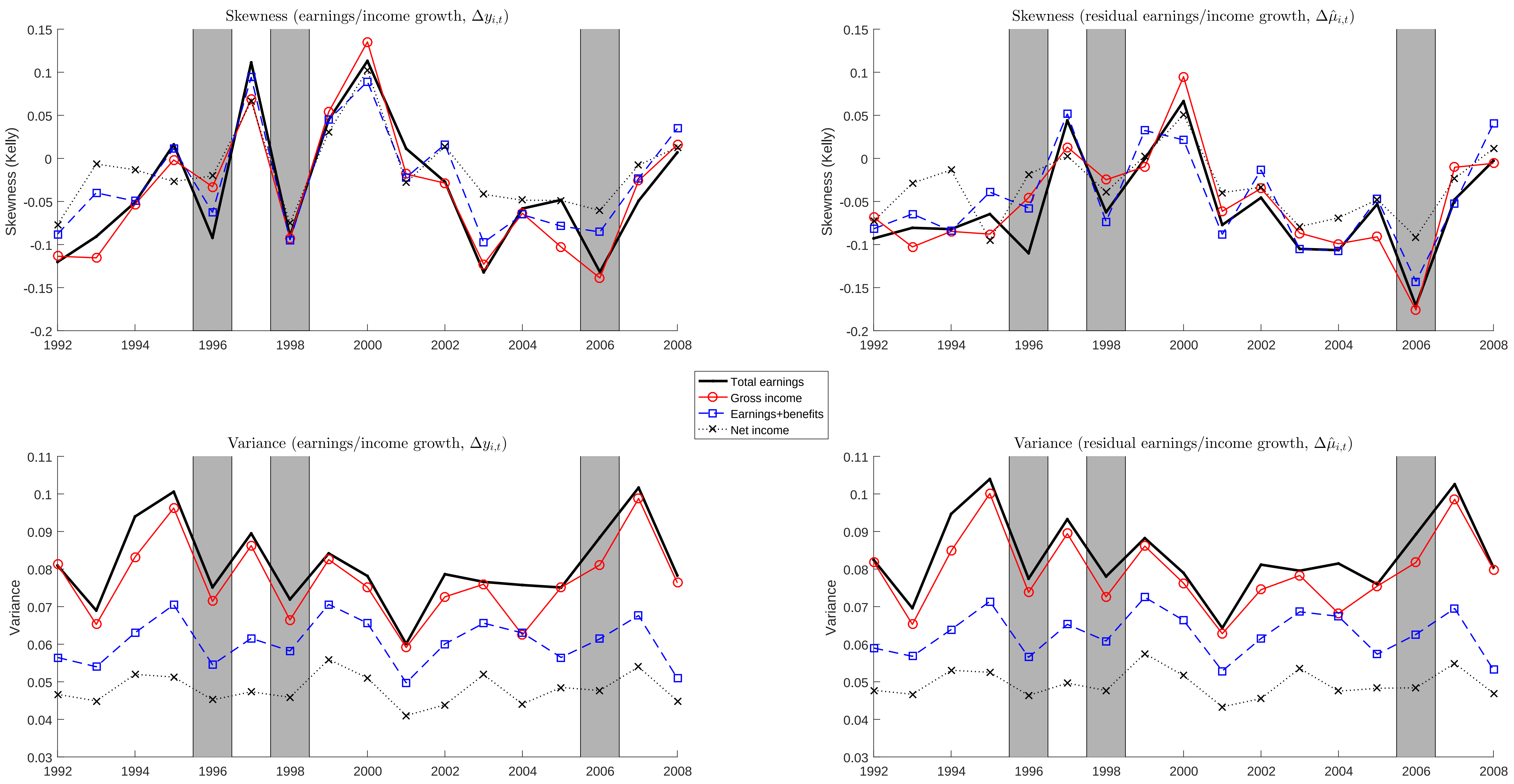
Figure 5: Skewness and Variance of Household, Head, Spouses Earnings Growth and Residual Earnings Growth



Appendix Figure C.1: Percentiles of Individual Earnings, Hours and Wages Growth Distributions



Appendix Figure C.2: Skewness and Variance of Household Earnings/Income Growth and Residual Household Earnings/Income Growth



Appendix Figure C.3: Percentiles of Household Labour, Gross and Disposable Income Growth Distributions