



University of the
West of England

Faculty of Business and Law

Measuring compliance with minimum wages

**Felix Ritchie, Michail Veliziotis,
Hilary Drew and Damian Whittard**

University of the West of England, Bristol, UK

*Economics Working Paper Series
1608*



University of the
West of England

bettertogether

Measuring compliance with minimum wages

*Felix Ritchie, Michail Veliziotis, Hilary Drew and Damian Whittard
Bristol Business School, University of the West of England, Bristol*

Abstract

Many countries have a statutory minimum wage for employees. There is a strong policy interest in knowing the degree of compliance with the law. Quantitative analysis is ideally suited to this, and many countries have rich datasets for employment research. However, identifying genuine underpayment of wages is not straightforward: data quality, statistical factors and processing errors can all contribute to the under- or over-estimation of the true level of compliance. The impact is exacerbated by the binary ‘yes-no’ nature of compliance.

We consider the statistical measurement of non-compliance in the UK. UK minimum wages have been extensively studied, using large-scale high-quality datasets whose characteristics are well understood and whose overlapping coverage allows triangulation of results. We focus particularly on apprentices: a survey of apprentice wages was introduced in 2011, throwing further light on measurement issues, even in a purpose-built survey instrument.

We identify several problems leading to under- and over-estimation of compliance rates. Some are well-known statistical or methodological issues, but others relate to the way that survey data is processed; this is rarely considered by data users. The binary nature of compliance makes such problems easier to identify and evaluate. In particular, we demonstrate the value of a very detailed knowledge of the data at crucial points in the distribution, and the importance of triangulation for understanding the reliability of estimates.

While concentrating on compliance with a statutory minimum wage, the paper has some wider lessons for the understanding the characteristics of large and complex datasets. We also show how the use of quantitative data can be used to effectively target complementary qualitative data collection.

JEL codes: C18, C55, C81, C83, J31, J38

Key words: minimum wage; non-compliance; measurement error; data quality

Acknowledgements

This paper brings together results from four research projects funded by the UK Low Pay Commission 2012-2016: Fry and Ritchie (2013), Ritchie, Whittard and Dawson (2014), Drew, Ritchie and Veliziotis (2015a, 2015b, 2016). We are grateful to LPC for the comments and discussion on those reports, to participants at the LPC’s research conferences and the Scottish Economic Society conference, and to discussants of our presentations.

Statistical results presented in this paper using ASHE or LFS data are Crown Copyright. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates. All statistical results in the paper are generated from ONS data by the authors, unless otherwise stated. Access to the data was given by the Office for National Statistics under project no. 12016. Access to APS data was granted by the Department for Business Industry and Skills.

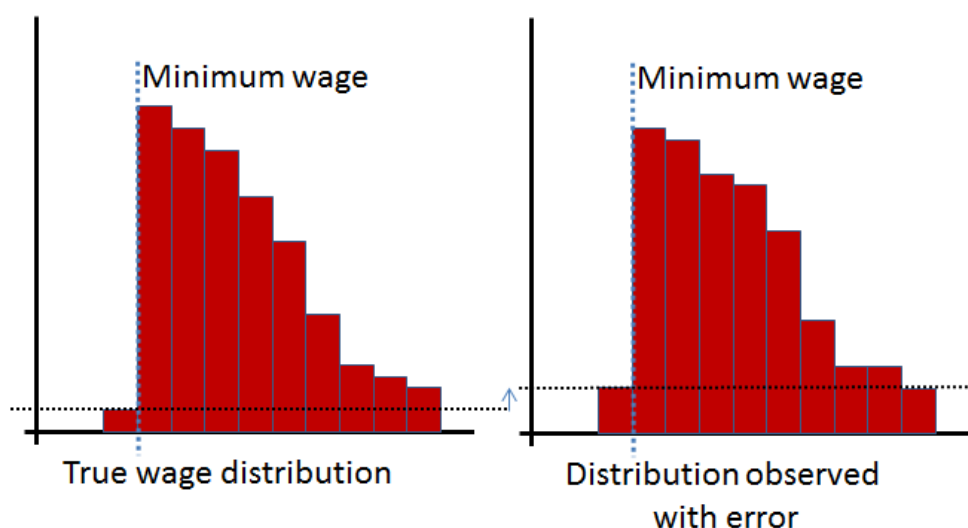
The views expressed in this paper are those of the authors and may not reflect the views of the Low Pay Commission, ONS or BIS. All errors and omissions are the responsibility of the authors.

1. Introduction

Minimum wages are widespread, particularly in high-income countries (HICs); 22 out of 28 EU countries (26 out of 34 OECD countries) had a statutory minimum wage in 2015, and most of the others had various wage floors determined by collective agreements (Garnero et al, 2015a; OECD, 2015). Minimum wages are seen by their supporters as a key part of the social infrastructure, and by some policy makers as a way to shift the burden of in-work social security expenditure from the state to the employer (Osborne, 2015). Ensuring that wages paid are compliant with the statutory minimum is therefore not just a legal necessity but important to social welfare policy. Enforcement agencies use estimates of non-compliance to allocate resources effectively.

Studies generally assume that non-compliance is accurately measured. However, the binary nature of the compliance measure (is the wage lawful or not?) can cause problems for analysis. Consider, for example, measurement error. In Figure 1 below, the true wage distribution, with a concentration of mass at the minimum wage, is measured with a randomly distributed error with mean zero. Estimates of the mean and median wage are unbiased but non-compliance will always be higher than the true value, because the increased dispersion of wages around the minimum wage level will lead to some observations falling on the ‘wrong’ side of the line.

Figure 1 Impact of measurement error on compliance



More generally, estimates of compliance can be extremely sensitive to the data accuracy. This does not just reflect data collection, but also the processing of the data; for example, in one case (detailed below), data collection processes leading to a rounding error of one penny increased estimated non-compliance rates by three percentage points. As Kampelman et al (2013) point out, in HICs non-compliance is typically very small and so these kind of errors can make a substantial difference.

As a result, the study of non-compliance can throw light on a number of aspects of statistical data production. Put simply, the sensitivity of non-compliance estimates to data quality highlights the impact of sample design, data collection, processing, and aggregation in ways which might not be apparent in analyses of continuous variables. Some of these issues reflect well-known problems, such as measurement error, but others come to light only through a detailed record-by-record analysis of the data, or knowledge of the production processes. In some ways, the analysis is closer to detective work than statistics.

Hence, this paper is concerned less with non-compliance levels per se, but with the accuracy of those estimates and what this tells us about the limits of quantitative analysis for guiding policy. Our conclusions are that a good knowledge of the data can pay dividends, and researchers need to understand the limits of what can be inferred from quantitative data. Of course, no statistician

would dispute either of the above, but in the case of non-compliance it is relatively easy to demonstrate just how important this is – and how easy it is to overlook the datapoint-by-datapoint analysis required for a good understanding.

Our investigation focuses on the measurement of non-compliance with the statutory National Minimum Wage (NMW) in the UK. The main reason for choosing the UK is its regulatory environment: recommendations to the UK government are made by the independent Low Pay Commission (LPC), which commissions a great deal of in-house and external research; as a result, the UK NMW is one of the most heavily researched minimum wages. The secondary data sources used for most NMW analyses have been extensively used over many years, and their general characteristics are well-known; nevertheless, the study of non-compliance has highlighted a number of new features of these surveys. In addition, non-compliance in the UK appears to be very low (Metcalf, 2007, describes this fact as ‘amazing’), and so small variations can be highlighted. Finally, the LPC devotes a considerable part of its annual research strategy to understanding non-compliance.

Within the UK, we concentrate particularly on the pay of apprentices, who only became eligible for a statutory minimum wage in 2010. We do this for four reasons. First, apprentice pay is slightly more complicated than the standard NMW, and this seems to be responsible, at least in part, for the non-compliance rates. Second, a dedicated survey of apprentice pay is available to measure non-compliance, and the comparison with other data sources can be instructive. Third, the survey was radically overhauled during the period under analysis and the reasons for the overhaul shed light on expectations of respondent behaviour. Finally, the NMW for apprentices is considerably lower than for any other group, and we believe that this in itself is an additional source of non-compliance through making rounding error more important.

The rest of this paper proceeds as follows. The next section reviews the relevant literature. Section three summarises the minimum wage framework in the UK and the quantitative data sources used for minimum wage analyses. Section four revisits the data production process and considers the problems that may arise at each stage and their implications for the estimation of non-compliance. Section five looks in detail at the specific case of estimating compliance rates for apprentices. Finally, section six concludes by considering the wider lessons for statistical analysis, particularly given the likely future use of more complex data sources.

2. Previous work on non-compliance

In their extensive survey of the literature on minimum wages, Belman and Wolfson (2014) report over 200 policy and academic papers published in English between 1992 and 2013 on minimum wages. However, a Google Scholar search indicates barely a handful of papers on non-compliance, and only two focusing on its measurement. Similarly, a literature review on non-compliance commissioned by the UK Low Pay Commission (LPC) largely turned up only reports and evidence submitted to the LPC itself (IPSOS-MORI, 2012).

2.1 Academic analyses

Most of the earlier papers (1970-2000) on non-compliance were written by economists keen to understand the drivers of non-compliance. The template was set by the US study of Ashenfelter and Smith (1979)¹, who specified a straightforward cost-benefit model of non-compliance and then evaluated it against evidence from microdata. Most subsequent works on non-compliance reference this work, using either secondary data or dedicated data collection (e.g. Weil, 2005).

¹ Gramlich et al (1976) carried out a very similar analysis on the same data, but did not develop a theoretical framework as Ashenfelter and Smith (1979) did.

For these papers, the accuracy of the non-compliance measure is of secondary importance as small variations in definition do not materially affect the broad functional relationships being identified (for example, between non-compliance rates and industry or occupation). Even on papers specifically estimating the probability of non-compliance at an individual level (e.g. le Roux et al, 2013; Garnero et al, 2015a,2015b; Ye et al, 2015) the quantitative and qualitative results do not seem to be sensitive to the particular definition of non-compliance used.

Although none of these papers focus on data accuracy, they do recognise that there are measurement problems in the data. Three solutions are generally taken, often together:

- Fuzziness: wages 'close enough' to the minimum wage may be considered as compliant
- Quality restrictions: only high-quality data are used
- Triangulation: data sources with different characteristics are checked for consistent findings

For example, Ashenfelter and Smith (1979) do all three: they treat a wage as being at the minimum if it is within +/- 5 cents, they restrict analysis to stated hourly wages rather than calculating wages for the non-hourly paid, and they compare results from both employee and employer surveys.

Since 2000, the focus of non-compliance analyses has shifted to looking at non-compliance in low- and middle-income countries (LMICs), particularly Latin America and sub-Saharan Africa (see, for example, Strobl and Wals, 2003; Yamada, 2012; Bhorat et al, 2015; Ye et al, 2015). These papers rarely consider issues concerning the accuracy of the data. One reason may be that the data are relatively limited; for example, Strobl and Walsh (2003) only had categorical data, while Ye et al (2015) only had annual wages and supplementary payments were not accurately identified.

However, a more likely reason is the very high rates of non-compliance in LMICs. Cross-country studies such as those of Basu et al (2010), Rani et al (2013), Bhorat et al (2015) and Randolph and Panknin (2015), show that compliance levels are well below 100%; in the case of Mali compliance is 10% (Rani et al, 2013). The high level of non-compliance means that small inaccuracies in the data are less important, as these cannot change results substantially. For example, Yamada (2012, p.46) notes that an allowance for measurement error does change the compliance rates noticeably, but with compliance below 40% in all sectors, findings are very robust to alternative specifications.

2.2 Policy analyses

If multivariate analysts are prepared to live with inaccuracies in the measurement of non-compliance as they do not fundamentally change the relationships uncovered, policy analysts interested in identifying the scale of any non-compliance problem are more concerned. For example, Kampelman et al (2013) repeatedly highlight the problem of measurement error and the fact that this will substantially increase non-compliance given the low rates observed in Europe. In response to this, they provide alternative measures of non-compliance where the true minimum wage is reduced by 25% to produce 'lower bound' estimates; Garnero et al (2015a) allow both 25% and 15% margins of error, although this is partly to allow for approximate compliance in countries where the minimum wage is bargained rather than statutory.

However, among bodies charged with the regulation of minimum wages, there seems relatively little interest in the issue, at least among the Anglo-Saxon countries. The US Bureau of Labor Statistics website has no analysis of non-compliance, only undocumented counts for hourly-paid employees; BLS(2014) argues that deriving an hourly wage leads to excessive measurement error. The NZ Ministry of Business Innovation and Employment also produces numbers but no analysis, as "it is not possible to identify whether [higher non-compliance] is caused by an increase in exemptions of the minimum wage, measurement error or non-compliance." (DLNZ, 2010, p27). The Australian Fair Work Commission has commissioned over fifty research reports since 2006 but only one (Nelms et al, 2011) directly addresses non-compliance. Moreover, both Antipodean ministries

note that there is insufficient data to distinguish genuine non-compliance from misreporting (Nelms et al, 2011; DLNZ, 2010).

This is in strong contrast to the UK; the literature review in IPSOS-MORI (2012) confirmed that most of what is known about non-compliance in the UK is derived from reports commissioned by the LPC, or from evidence submitted to the LPC's annual consultation exercise:

"...although it has rarely been an explicit part of our remit from the Government, we have always reported on the evidence gathered on compliance and enforcement matters through our consultation processes, and regarded this as an integral part of our role in advising on the minimum wage." LPC (2015), p.199.

The LPC commissions external analyses of compliance, as well as carrying out its own analysis. LPC and external researchers tend to use the same secondary datasets for quantitative analysis. Hence, both the data and the prevalence of non-compliance are well understood in the UK. This reality forms the basis for the research presented in this paper.

The LPC's first report since the introduction of the NMW (LPC, 2000) devoted five pages to understanding non-compliance; in the latest report (LPC, 2015), this has expanded to 35 pages based on both qualitative and quantitative research. The LPC's analyses explicitly reference concerns over the accuracy of non-compliance estimates, particularly since Griffiths et al (2006) and Ormerod and Ritchie (2007) noted problems of processing and rounding. Le Roux et al (2013) were the first to explicitly test the robustness of non-compliance estimates to data inaccuracies, and concluded that, like earlier academic analyses, multivariate relationships were not sensitive to these data limitations.

2.3 The meaning of 'compliance'

Bhorat et al (2013) are unusual in focusing on the particular meaning of 'non-compliance'. They note that there is a qualitative difference between one or two cents or pennies below the minimum wage and being paid a dollar or euro below. Hence, they propose a flexible weighting scheme such that trivial violations are ignorable, and which usefully includes counts and linear summations among its special cases. Applying their methodology to data from South Africa, they find a correlation between the number of violations and the scale. Ham (2015) applies the same method and comes to the same conclusion using data from the Honduras.

2.4 Summary

Although non-compliance has been discussed by many researchers, few have looked at the non-compliance measure per se. Early empirical studies (1970-2000) focused on the drivers of non-compliance, usually based on US data. In these studies, non-compliance rates of 20%-30% meant that minor inaccuracies in the data did not qualitatively change the relationships uncovered. Similarly, as the focus of interest moved to compliance in LMICs after 2000, precision over the measurement of compliance was swamped by the high non-compliance rates and more general concerns over data quality.

Regulatory bodies also seem relatively incurious about non-compliance rates, although in some cases this seems to be driven by the lack of data to investigate alternative hypotheses. The exception to this is the UK LPC, which actively researches compliance levels. The UK results will inform the rest of the paper.

3. Minimum wages in the UK

3.1 The NMW and the LPC

The National Minimum Wage (introduced into the UK in 1999). The NMW is compulsory for all employees aged 16 and over, and the wage rates are age-related. Not all workers were initially covered: 16-17 year-olds were not covered until 2004, and apprentices did not have a minimum wage until 2010. Table 1 presents the relevant rates for each year and group.

Table 1 NMW rates by applicable group

Rate from...	'Adult' Aged 21+	'Development' 18 to 20 y.o.	'16-17yo' Under 18	'NMWAR' Apprentices
April 1999	£3.60	£3.00		
October 2000	£3.70	£3.00		
October 2001	£4.10	£3.20		
October 2002	£4.20	£3.50		
October 2003	£4.50	£3.60		
October 2004	£4.85	£3.80	£3.00	
October 2005	£5.05	£4.10	£3.00	
October 2006	£5.35	£4.25	£3.30	
October 2007	£5.52	£4.45	£3.40	
October 2008	£5.73	£4.60	£3.53	
October 2009	£5.80	£4.77	£3.57	
October 2010	£5.93	£4.83	£3.64	£2.50
October 2011	£6.08	£4.98	£3.68	£2.60
October 2012	£6.19	£4.98	£3.68	£2.65
October 2013	£6.31	£5.03	£3.72	£2.68
October 2014	£6.50	£5.13	£3.79	£2.73
October 2015	£6.70	£5.30	£3.87	£3.30

The original boundary for the adult rate was 22 years of age, but this was reduced by a year in October 2010. The Apprentice Rate (NMWAR) is unusual in that it has both an age and year of training component. The NMWAR is payable for apprentices on their first year of training or if they are aged 16-18; otherwise, the standard age-specific NMW applies. Note also that the age boundary for the NMWAR does not align with that of the standard NMW.

The Low Pay Commission (LPC) was set up in 1998 to review the evidence on the impact of the NMW and make recommendations on the level and structure of the NMW. The LPC also produces the formal population estimates of non-compliance. The Commissioners are advised by a research team who carries out analyses and commissions external reports. The research team also carries out primary data collection, mainly qualitative studies, to provide context and corroboration or denial for the quantitative studies.

The LPC reviews the research evidence annually. This review is available on the LPC website, as are all the commissioned research studies.² As a result of these different strands of analysis carried out over several years in changing economic conditions, the evidence base for the LPC recommendations is broad, detailed, and transparent, and is cumulatively summarised in the LPC's Annual Reports.

² See the LPC's website at <https://www.gov.uk/government/organisations/low-pay-commission>.

3.2 Data sources

Two large-scale surveys from the Office for National Statistics (ONS) provide much of the quantitative evidence: the Annual Survey of Hours and Earnings (ASHE), and the Labour Force Survey (LFS); see Ritchie et al (2014, part A) for an overview. Griffiths et al (2006) offer a detailed critique of the pay measures. The data sources are summarised below.

ASHE (and its predecessor, the New Earnings Survey or NES) is an annual longitudinal random sample of 1% of employees with data supplied by their employers. In general, the dataset is seen as reliable, accurate and representative of formal employment (Milton, 2004; Fry and Ritchie, 2013). Around 175,000 employees are sampled annually and the data are linked to employer characteristics. Detailed pay and hours data are available, but age and gender are the only personal characteristics recorded. The main pay variable is *derived* by dividing actual pay by actual hours; but employers are also asked to provide a *stated* hourly wage if the employee receives one.

The Labour Force Survey (LFS) is a quarterly survey of roughly 60,000 individuals, of whom around three quarters are employed. It has very detailed personal characteristics, such as ethnicity, nationality, level of education etc. Pay and hours are reported by the employee and can generate a *derived* wage rate, but concerns over the accuracy of the data means that the preferred pay measure is the hourly rate *stated* by the employee (Fry and Ritchie, 2013). Respondents are asked to provide pay information by referring to relevant documentation (e.g. a payslip), but only a small proportion does so. This seems to be important for the accuracy of estimates (Ormerod and Ritchie, 2007; Ritchie et al, 2014).

Prior to 2004, concerns about the accuracy of the NES (which was thought to underestimate non-compliance) and LFS (overestimation) meant that the LPC's estimates of non-compliance were an average of the NES and LFS results. With the redesign of NES as ASHE specifically to address low pay estimates, ASHE data were used only for national estimates of non-compliance. However, LFS data continue to be used for breakdowns by personal characteristics (e.g. ethnicity, nationality, education, disability etc.), as these are only available in the LFS. Because only a proportion of respondents provide stated wages, missing values are estimated at the individual level using a multiple imputation process developed by the ONS. This process has been strongly criticised (see e.g. Dickens and Manning, 2004; Ritchie et al 2014, part C).

In 2011, the UK Department for Business, Innovation and Skills (BIS) commissioned an Apprentice Pay Survey (APS) to monitor specifically the impact of the new NMWAR. This was done because neither ASHE nor LFS had sufficient information on apprentices: numbers were small, no training data were gathered, and the information necessary to calculate the appropriate rate was missing. The APS was sent to apprentices, who were selected randomly from a national list of apprentices at BIS.

The APS was run in 2011 and 2012. There were a number of problems with the survey (summarised in LPC, 2015 and Drew et al, 2015a), and was completely redesigned for the 2014 round. The revised survey is believed to be more reliable (Drew et al, 2016).

3.3 Non-compliance in the UK

LPC (2015, p.p. 199-234) summarises the current view on non-compliance in the UK. Overall non-compliance with the NMW has been relatively stable at about 1% of the employed workforce for several years. It appears to be higher for younger workers (under 21), and for certain professions (hairdressing, child care, social care, retail). However, since the start of the recession in 2008, non-compliance amongst the under-21s seems to be rising substantially: from being relatively stable until 2009 at round 3.5%-4%, it has steadily increased and is now running at 8.5% for 16-17 year olds and 7% for those aged 18-20 (LPC, 2015, Figure 3.12, p133).

The large and persistent increase of non-compliance among younger workers since the start of the recession is a cause for concern, but LPC (2015) argues that most of this is due to the rising

number of apprentices who have much lower compliance levels (see below). Excluding apprentices, non-compliance rates for young workers are more stable but still substantially higher than for those on the 'adult' rate.

Three elements of pay and hours complicate the estimation of non-compliance: the accommodation offset, piece work, and non-work time. Employers are allowed to offset wages at a fixed daily rate if accommodation is provided, while minimum wages for piece work are calculated by estimating a 'fair' amount of time to complete the work. Finally, travel time and rest breaks should be included in the calculation of hourly pay. Each of these elements adds complexity to the calculation of the appropriate wage. The LPC accepts that most non-compliance is due to mistake rather than deliberate avoidance.

One area that has been a particular cause for concern is the pay of apprentices. The 2012 APS shows non-compliance rates of around 50% for 19-20 year old apprentices, while even higher rates are observed for some occupational sub-groups such as hairdressers (Drew et al, 2015a). As will be discussed below, this high level of non-compliance is almost certainly the result of an error caused by survey design, but even so non-compliance rates for apprentices are significantly higher than for other workers.

The overall non-compliance rate of 1% has been challenged by groups who argue that the most disadvantaged groups are excluded from the analysis, a position acknowledged by the LPC. We return to this below in our consideration of sampling.

4. Identifying genuine non-compliance in principle

Consider first the LPC's problem. It aims to:

- Identify the amount of non-compliance.
- Determine the causes of non-compliance (in particular, whether it is deliberate or not).
- Formulate an appropriate and practical policy response.

The LPC's policy responds to what employers intend to pay and what they do pay. However, there are several processes which occur between employer decisions and LPC policy based on observable evidence:

- 1) Employers decide what to pay workers
- 2) Employers pay workers
- 3) A subset of those worker-employer interactions are sampled
- 4) Hours and earnings information is gathered from those sampled
- 5) Data are processed into suitable measures
- 6) Data are weighted
- 7) Compliance is calculated
- 8) Inferences are drawn
- 9) Policy decisions are made

There is much scope for error between employer actions – even the most basic one that the wage employer intend to pay may not be the one that they actually pay – and the statistical conclusions that the LPC has to work on. In this section we consider each of the problems posed by processes (3) to (8), using the UK environment as an example; in the next section we turn to the specific problem of measuring a non-compliance rate, looking at apprentice pay.

4.1 Sampling

The first concern is that the sampling does not accurately represent those on or below the minimum wage. Employers paying below minimum wages have few incentives to respond to official surveys.

Employees being paid below minimum wages are likely to be in jobs where the employer is 'powerful', in a psychological sense, and so providing potentially negative information about that employer might be impractical. Qualitative analysis carried out by the LPC and others, and evidence provided through consultations, suggests non-compliance is much more widespread amongst groups such as migrant workers, agricultural labourers, or family workers, particularly if these workers are illegally employed (LPC, 2015). The workers in these groups are likely to face substantial pressure to be discouraged to respond to any official request for information.

There are also concerns about *de facto* employees wrongly classified as 'self-employed' specifically to avoid employment regulations. For example, in the UK LFS, individuals are asked to self-report their employment status; it is already known that some LFS information is inaccurate (for example, by comparing LFS data with other surveys; see Ormerod and Ritchie, 2006), and employment status is not easy to determine in the case of agency contracts without knowing the specific contract. By its nature, the extent of non-compliance because of these reasons is unknowable.

Finally, there is the question of timing. The UK NMW changes in October each year (except 1998 and 2016). Not all wages change immediately, and this can cause problems. Consider the LFS wage data gathered in October and which fall below the new NMW, but not the old one. There are three possibilities:

- The 'reference week' is the end of September, when the old NMW applied (the wage is compliant)
- The uprating has been delayed but will be implemented with back pay (the wage is not compliant at present, but the issue will be resolved)
- The uprating has not been paid and will not be backdated if it is paid (the wage is non-compliant)

The second case is problematic: it is not clear whether this should be marked as 'compliant' or not; nor does the LFS collect information later in the year to distinguish delayed payment from non-payment. Ormerod and Ritchie (2007) noted that simple non-compliance rates fall continuously through the year, but that the pace of this fall settles down after two quarters.

In summary, it is likely that non-response is concentrated amongst the lowest paid; some groups (and, particularly, the illegally employed) do not appear in the sampling frame at all; and the timing of data collection will affect the outcome.

4.2 Data quality

4.2.1 Getting 'honest' responses

The standard assumption is that employer data are of higher quality since they are derived from pay records. There is some evidence supporting this in the UK (Milton, 2004; Griffiths et al, 2007). However, this assumption has also been questioned: as paying below the NMW is an offence, employers may not want to submit such non-compliant wages, and they may adjust the data before reporting (Garnero et al, 2015b).

LPC (2015) also notes the scope for collusion between employer and employee: an employee may be paid below the NMW but the reported hours may at the same time be adjusted downwards to meet the NMW threshold, while also allowing the employee to claim welfare benefits based on part-time working. Metcalf (2007) provides some anecdotal evidence. He notes that in family-operated businesses, an hourly wage is not relevant: workers receive a daily or weekly wage and are required to put the hours in as necessary. Hours are then adjusted as necessary if reporting is requested by an authority.

The scale of such deliberate misreporting is fundamentally unknowable, because by definition the data collected are all that the respondent feels able to deliver.

4.2.2 Rounding

Independently of whether data are honestly provided, there is the question of how accurate the data are.

For example, Ormerod and Ritchie (2007), Fry and Ritchie (2013) and Ritchie et al (2014) demonstrate that the rounding of wage data by employees is a well-established phenomenon in the UK, and it has an impact on non-compliance levels. Fry and Ritchie (2013) go further, predicting distributions for the LFS and ASHE based entirely on where the minimum wage was set relative to a 'focus point'; for example when the rate was £4.98/hour, they predicted that most employees would report a wage of £5.00 per hour. Their estimates were too conservative: *all* employees reported £5.00 or above, despite employer data showing considerable numbers at £4.98.

There is strong evidence that rounding is persistent, time-scale invariant, and occurs at the point of data collection: hourly-paid workers round hourly wages, the weekly paid round weekly wages, and salaried workers round their salaries; while checking documentation when responding to the survey reduces the chance of rounding (Ritchie et al, 2014; Drew et al, 2015). This findings are so far restricted to the UK but the persistence of such results suggests that this is a human phenomenon which would be reproduced in other countries. Le Roux et al (2013) show that this can have a considerable impact on the compliance rate.

4.2.3 Other cognitive response problems

Notwithstanding the problems of dishonest or rounded responses, respondents may simply fail to provide accurate information; for example, through recall bias, inability to account for breaks accurately, or failure to understand the questions being asked. Sometimes these may be amenable to retrospective adjustment. For example, Griffiths et al (2007) show that a number of ASHE respondents fail to understand the different wage measures; however, in that case it is possible to improve compliance estimates by manual adjustment of the data.

4.2.4 Non-standard earnings

In the UK, some workers are paid piecework rates, others are eligible for the time spent travelling to work, and all are eligible for an accommodation offset. In general across industrialised countries, this information is not available, and so accurate rates cannot be calculated.

4.2.5 Summary

In summary, data may be collected inaccurately, dishonestly, or not at all. In some cases it is possible to predict the direction of the impact on compliance (dishonesty reduces non-compliance, rounding reduces or increases non-compliance but in a predictable way etc.) but in general the impact is unknown. This uncertainty is reflected, for example, in the LPC's preference for the term 'underpayment' for observed non-compliance (source: personal communication).

4.3 Processing

Most researchers are familiar with the statistical problems noted above. However, few consider the processing of the data which can add either error or spurious accuracy. For a yes/no question such as compliance with a minimum wage, minor errors can have disproportionate effects. For example, Griffiths et al (2007) consider the problem of reproducing national aggregates from micro data. They demonstrate that rounding data in calculations to five decimal places instead of four can increase non-compliance rates from around 1.2% to 1.7%. They also note the importance of decimal places

when transferring between statistical systems: exporting SAS data files to Stata at 2-5 decimal points did not substantially affect non-compliance estimates, but 6 decimal places did.

A difficulty is spotting this problem because it is not clear where to look at. Statistical offices are not normally resourced to look at minor variations: in recent years the dominant model has become 'statistical editing', where potential errors in data are only investigated if they substantially change statistical outputs. This generally applies to very large respondents, or ones in very small sample groups. Neither of these applies to low wage employees, and the wage estimates that ONS produces are not materially affected by such errors. The non-compliance estimates may be affected, but these are produced by the LPC, not the ONS.

To address this, the ONS has a specific rule: check input data if it leads to an hourly wage being below the NMW. However, it is important to note that the ONS only checks the accuracy of the data recorded on its form, not whether the respondent arrived at the information correctly.

With household data, there is a slightly different issue. We have observed household data collection by ONS, and noted that interviewers do not sometimes record the full detail offered by respondents. However, it is debatable how important this is, given the other problems in answering accurately. The ONS did change its interviewer instructions after the publication of Ormerod and Ritchie (2007), but this appeared to have had little impact.

Although this appears to be an intractable problem, the solution in terms of non-compliance is straightforward. Analysts, including the LPC, round wages to the nearest penny; this has, historically, seemed to address these processing issues. Note that the small adjustment is made in the UK because the data are generally assumed to be accurate; in contrast, Garnero et al (2015a, 2015b) treated wages up to 25% below the minimum as 'compliant', to allow for measurement error.

4.4 Weighting

All surveys contain weights to produce population estimates. These are based upon the ex ante sampling weights, adjusted for actual responses. The ex ante weights should reflect the expected sampling problems addressed above. The ex post adjustments reflect actual sampling rates, compared to the expected population distribution.

There is often limited opportunity to verify the accuracy of ex post sampling weights. For example, in the UK there are three sources of information on the workforce: ASHE, LFS and the decennial Census. However, these are not independent: ASHE weights are derived from the LFS, whose weights are in turn derived from the decennial Census, with some inter-censal adjustment. Hence, while these weights are the 'best available estimate', triangulation between these sources to establish a 'robust' estimate is not statistically valid. It is possible to use administrative records (such as tax information) to provide an independent source, but this tends not to have the detail on respondent characteristics to allow stratification of estimates.

4.5 Calculation of the non-compliance rate

One statistical issue is that of the denominator for non-compliance calculations. Typical measures are the proportion non-compliant over the whole workforce (or at least the relevant age group). An alternative is to consider a subset closer to the minimum wage. The rationale is that the NMW is not a relevant concept for high-earners: non-compliance should instead answer the question "Out of the very low paid, how many of those are not even getting the statutory minimum?" The difficulty here is that the number of 'low paid' employees is a subjective measure. Should the denominator include all those at or below the minimum wage, or should it include some above the minimum?

The LPC defines a 'minimum wage worker' as one earning the NMW plus 4p (5p band including the rate); in its 2016 report the LPC began reporting non-compliance as a proportion of both all workers and 'minimum wage workers'. However, Fry and Ritchie (2013, p6) argue that this

ignores the human propensity to pay (and report) at rounded numbers; they recommend using “NMW up to the next 10p absolute value”. Under this definition, an adult worker would be a “minimum wage” one if being paid £6.00 in 2011 when the adult NMW was £5.93, whereas the LPC definition misses this. This should be a less volatile measure as it reflects how the mass of observations just above the NMW fluctuates with the penny value of the NMW.

Overall, it is clear that the definition of the preferred ‘non-compliance rate’ is not unambiguous.

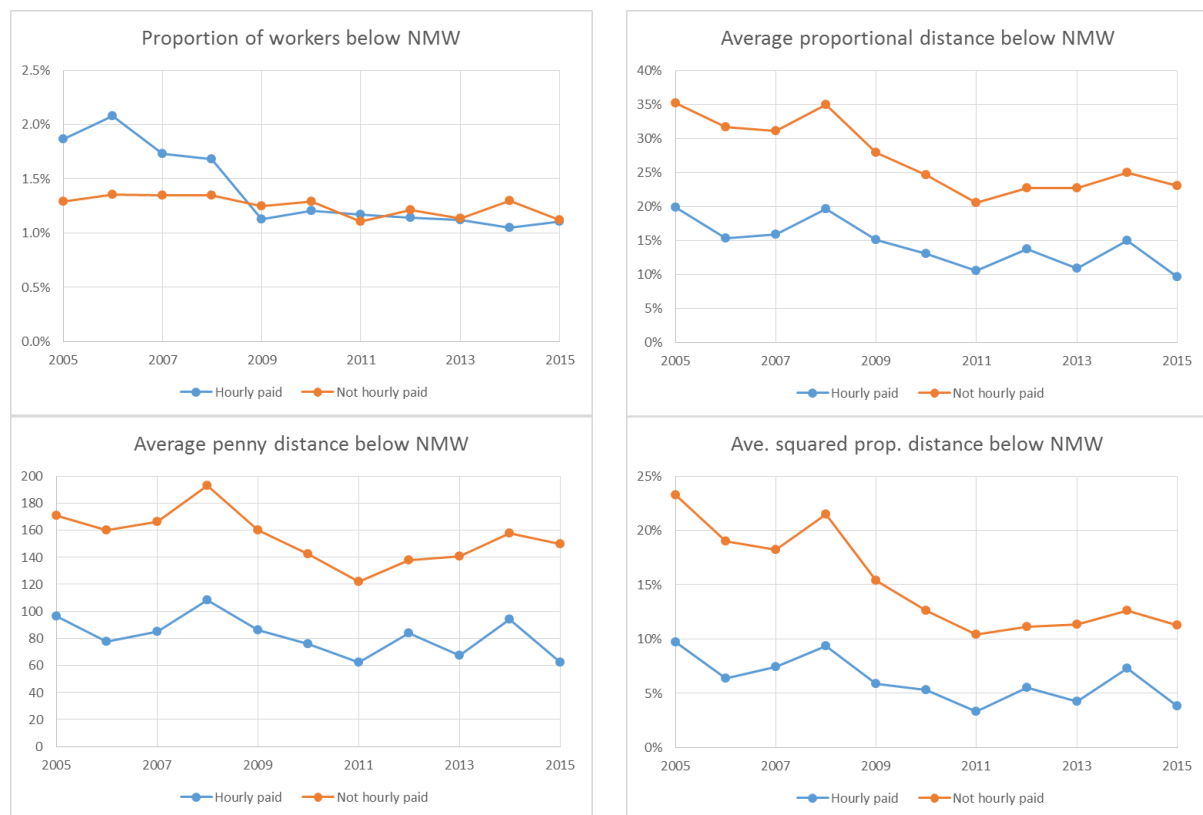
Moreover, Bhorat et al (2013) argue that any ‘rate’ is of limited information as it does not capture the scale of the problem, and instead suggest a measure where each wage is weighted with its distance from the MW. This has not been adopted by any agency yet, although it would, among other things, neatly deal with the problem of small inaccuracies in the data.

Bhorat et al (2013) suggest using a measure of the form:

$$m_t = \sum_{i \in w_{it} < MW_{it}} \left(\frac{w_{it} - MW_{it}}{MW_{it}} \right)^\alpha / N_{i \in w_{it} < MW_{it}}$$

where the measure of interest in period t, m_t , is calculated by summing the size of the gap from the minimum wage from all those earning below their relevant minimum wage ($w_{it} < MW_{it}$). The parameter α weights the results, with $\alpha = 1$ creating a simple average distance of wages below the MW and higher values placing more weight on large underpayments.

Figure 2 shows the result of calculating these indices for the UK for those eligible for the standard adult minimum wage. It also shows the non-compliance rate, and the average penny value (not proportion) below the NMW.



The top left panel shows that non-compliance hovers around 1.5% in the UK for those on the adult MW. For the non-hourly paid it is almost flat; for the hourly-paid, the rate dropped sharply until 2009, and appears flat since then.

The higher non-compliance rate for the hourly paid in the early years is surprising, as most UK studies show that, all other things being equal, the hourly paid are much more likely to earn at or above the minimum wage. This illustrates the problem of choosing the denominator when calculating measures of non-compliance. Hourly paid workers are much more likely to be on low wages; high earners are typically salaried. Therefore the non-compliance rate for the hourly paid is actually asking “what is the non-compliance rate amongst low earners” whereas the non-compliance rate for the non-hourly paid asks “what is the non-compliance rates amongst the mostly middle and high earners?” This is why LPC(2016) began reporting non-compliance as both a proportion of the workforce and of the ‘minimum wage’ workforce.

The two right-hand panels show that, for this group at least, weighting proportional distances gives much the same result as a simple average of the proportional gap; in other words, underpayment is clustered rather than widely dispersed and this persist through time. Both seem to show that, for both the hourly paid and non-hourly paid, the proportion gap fell from 2005 to 2011, but then appears to be constant.

Finally, the bottom left panel shows that the average amount of underpayment has stayed fairly constant over time, despite the fact that the adult MW in the UK has increased from £5.05 to £6.70 in this period, a 33% increase. This lends support to the argument of Ritchie et al (2014), for example, that round numbers rather than proportional differences drive wage decisions.

Alternative indices therefore do add some value to the understanding of non-compliance, but it is clear that the value comes from comparison: either being able to generate them over a period of time, or looking at the figures from other countries. In the UK, it is also possible to compare the non-compliance rates for different MWs as well. Interpretation is somewhat hampered by the novelty of most of these numbers, as these are, to our knowledge, the first ones produced.

4.6 Drawing inferences

What inferences can be drawn from compliance measures? Most work on the minimum wage is carried out by economists, who tend to use data to test pre-identified hypotheses, and then interpret results with reference to those hypotheses. This approach has been criticised by statisticians, who argue that this approach encourages confirmation bias in analysis.

More generally, econometric or statistical analysis is often plagued by the ‘identification problem’: several alternative theories are consistent with the same statistical finding. For example, the stylised fact that more education is associated with higher wages is consistent with human capital, search and Marxist theories of the labour market.

In the UK, the presence of both ASHE and LFS estimates provides an opportunity to reduce over-interpretation of results by triangulating (unweighted) findings; differences can be exploited to test hypotheses more effectively. For example, Ritchie et al (2014) show that, once genuine rounding behaviour by firms is taken into account, measurement error in the LFS due to rounding appears to be entirely random. This is entirely consistent with theories of universal psychologies, but it requires the two different sampling mechanism of the two different surveys to be feasible.

However, it is rare to find clear results unambiguously aligned to theory. Le Roux et al (2013), for example, find that the different data sources tell opposite stories concerning the impact of the recession on non-compliance.

4.7 Summary

We have briefly covered a number of factors affecting the estimates of non-compliance in the UK; and it is clear that these partly arise from a detailed analysis of the data on a point by point basis. We now consider in more detail a case which has been exercising the UK government considerably in recent years: the pay of apprentices.

5. Non-compliance among UK apprentices

The NMW Apprentice Rate (NMWAR) was introduced in 2010. The NMWAR is payable to all apprentices in their first year of the apprenticeship; after that, those aged under 19 stay on the NMWAR, whereas older apprentices revert to their age-specific NMW. The legislative framework applying to apprentices is therefore more complicated, as it requires knowledge of both age and length of training. Measuring hours for apprentices is also more complicated: they should have a minimum number of on- and off-site training which should all be included in their paid hours.

Prior to 2010, apprentices were exempt from the regulations. This may in itself have led to overestimates of non-compliance, as (unrecorded) apprentices may appear in the data as workers begin paid below their minimum.

Information on the pay of apprentices comes from two sources:

- The Apprenticeship Pay Survey (APS) was specifically commissioned by the Department for Business, Innovation and Skills (BIS) to investigate apprentice pay. It was a random sample of all those registered for an apprenticeship in the UK, with different levels of coverage across the four countries of the UK. Highton et al (2012) and Highton (2013) describe the 2011 and 2012 APS, respectively. The 2011 and 2012 surveys were heavily criticised (Drew et al, 2015a provide a detailed analysis), however, and in 2014 a completely redesigned APS went into the field; see Winterbotham et al (2014). The reasons for this change are discussed below.
- The APS is compared against ASHE. From 2013 on, ASHE also began to collect the minimal information necessary to identify apprentices. In contrast, there is negligible information on apprentice wages in the LFS.

Non-compliance for apprentices is much higher than for other workers (see Table 2). As well as being higher overall, the rates are higher for those not on the NMWAR (16-18 y.o. or in their first year of apprenticeship), particularly for those aged 19-20. These findings are consistent across different datasets and combinations of characteristics (such as framework or gender).

Table 2 Overall non-compliance rates for apprentices (in % of total apprentices)

Eligible NMW	Non-compliance					
	APS			ASHE		
	2011	2012	2014	2013	2014	2015
AR (16-18 or first year)	11.2%	16.5%	10.2%	3.0%	2.4%	1.1%
YDR (19-20, second year)	46.9%	54.7%	33.0%	10.7%	13.4%	7.5%
Adult (21+, second year)	27.0%	35.5%	30.5%	5.4%	6.7%	5.8%
Overall	19.8%	29.4%	15.8%	5.0%	5.5%	3.3%

Source: Authors' calculations; APS 2011, 2012 and 2014, weighted data; ASHE 2013-15, unweighted data.

We now proceed with the examination of the issues identified in the previous section, as applied to the case of the APS and the apprentice pay in general.

5.1 Sampling

A major criticism of the analysis of non-compliance using government surveys is that these do not fully incorporate the 'grey', cash-in-hand or illegal economy. Qualitative analysis carried out by the LPC and others, and evidence provided through consultations, suggests non-compliance is much more widespread amongst groups such as migrant workers, agricultural labourers, or family workers, particularly if these workers are illegally employed (LPC, 2015). There are also concerns about *de facto* employees wrongly classified as 'self-employed' specifically to avoid employment regulations. By its nature, the extent of non-compliance because of these reasons is unknowable.

However, for the APS this problem appears to be addressed effectively. The population of apprentices is known with a great deal of certainty: only those registered with BIS count as apprentices, and this is, broadly, the sample frame for the APS.³ The APS is voluntary, and response rates are relatively low. Nevertheless, Highton et al (2012) and Winterbotham et al (2014) argue that the responses are representative of the apprentice population.

However, there is a major problem concerning the timing of the survey. The 2011 and 2014 surveys took place in the middle of each year, when minimum wage adjustments tend to have settled down (Fry and Ritchie, 2013). In contrast, the 2012 APS went into the field in October 2012, just after the minimum wage had changed. It was therefore impossible to identify whether wages being paid at the previous year's rate were legitimate or not.

While the APS is seen as representative, the number of apprentices identified in ASHE seems far too low. ASHE normally samples around 0.75% of the working population, but for apprentices the rate is less than half of that (see Table 3).

Table 3 Sampling rates in ASHE

	2013	2014	2015
Registered apprentices in year	868,000	852,000	871,000
Estimated apprentices, point-in-time	592,000	581,000	594,000
ASHE observations	1,508	1,863	1,982
Sampling rate	0.25%	0.32%	0.33%

Source: ASHE data, authors' calculation; registered apprentices from SFA (2015). Point-in-time apprentices estimated by adjusting to weighted APS estimate (581,000 in 2014)

It seems unlikely that the apprentices in ASHE are missing randomly. First, these are disproportionately likely to be made up of low earners changing jobs frequently (Knight, 2010). Second, employers with poor administrative processes or using cash-in-hand payments are less likely to be identified by the HMRC. Third, Drew et al (2015b) observed that individuals who start an apprenticeship with their current employer are more likely to be paid at or above the relevant minimum wage than those starting with a new employer. Individuals who remain at their employer for longer are also more likely to be identified in ASHE, which uses "latest known employer" information from the HMRC to trace respondents.

This may explain why the ASHE non-compliance rate is similar to that calculated for those who use payslips to provide information in the APS 2014: we would expect these APS respondents to be in the same subset of organised PAYE-paying employers. Table 4 shows the level of non-compliance in the APS by whether documentation is used or not.

Table 4 Extent of non-compliance, by APS source

	% of apprentices earning below their legal minimum
Baseline sample (<i>N</i> =6,567)	15.8%
Payslip respondents (<i>N</i> =2,698)	12.0%
Non-payslip respondents (<i>N</i> =3,869)	20.7%
Both pay and hours from payslip (<i>N</i> =1,074)	5.7%
Reporting hourly pay (<i>N</i> =517)	3.8%

Notes: Source APS 2014, authors' calculations; weighted data

³ This is not exactly the case. You can also be an apprentice for minimum wage purposes if you have an 'apprentice contract', which is a historic anomaly and not directly connected to the government training scheme. Although the number of apprentices not on registered schemes is unknown, the perception is that these are few and, hence, the APS is representative of the apprentice population.

One can see that when information both hours and pay information is provided on a payslip, non-compliance rates in the APS and ASHE become much more similar.

In short, those apprentices recorded in ASHE are likely to be those in stable, long-term employment with an employer, with good and up-to-date record-keeping. Hence, while the APS and ASHE broadly agree on the non-compliance rates for fully documented earnings, the low sampling rates for ASHE are likely to be biased towards compliant observations; hence, the ASHE non-compliance data can be taken as a ‘lower bound’ for non-compliance.

5.2 Data quality

The 2011 and 2012 APS asked for wage data at the payment level: for hourly-paid workers, an hourly wage was recorded, for weekly-paid a weekly wage, and so on. Standard hours were also recorded, so that an hourly wage could be derived for the non-hourly paid.

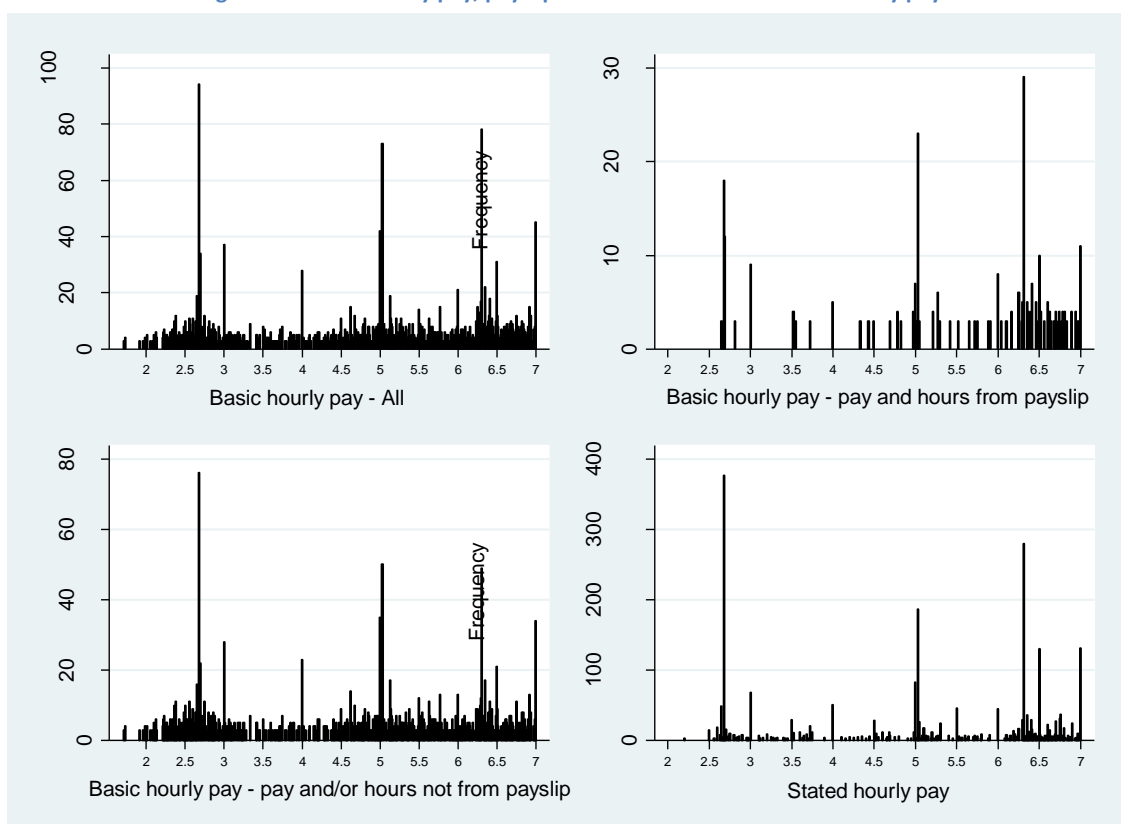
There is a substantial difference in non-compliance between the hourly and the non-hourly paid. Table 4 records the relevant breakdown.

Table 5 Non-compliance rates in APS, by pay period

	2011 APS	2012 APS
Hourly paid	5.0%	20.7%
Not hourly paid	24.8%	33.5%
Full sample	19.8%	29.4%

Source: APS data, authors calculation; weighted

Figure 2 Derived hourly pay, payslip information and the stated hourly pay



Source: Authors' calculations; APS 2014, unweighted data, stated hourly pay sample

As with the other employee surveys in the UK, wages in the APS are rounded at the pay period, which may account for some of the disparity in responses. However, the main cause for the

difference between the hourly and the non-hourly paid seems to be a mismatch between hours and earnings: the APS derived wage has a much wider distribution than the hourly rate. See Figure 2 for the 2014 data; similar results occur for 2011 and 2012.

Part of the confusion may be that the 2011 and 2012 APSs asked for both paid hours and training hours, on- and off-site. Because of this, there is great ambiguity on how these questions should be answered, and, hence, the accuracy of the derived value for the hourly pay is questionable. This may explain why the hourly paid non-compliance rate is so much lower: it does not need an accurate estimate of hours. Some further support for the idea that hours is the main cause of the problem comes from comparing non-compliance rates by type of training received. Table 5 reports the relevant estimates.

Table 6 Non-compliance rates in APS by training

	2011 APS	2012 APS
Some off-the-job training	32.5%	37.9%
No off-the-job training	17.7%	26.1%
Some on-the-job training	22.9%	32.7%
No on-the-job training	12.5%	21.2%

Source: APS data, authors' calculations; weighted.

These concerns were raised in Drew et al (2015a), and led to the complete overhaul of the APS. Interestingly, the 2014 APS only asked for total hours and not a breakdown by training or not. The rationale seems to be that trying to get accurate detail had been shown to fail, and it was better to concentrate on a better, simpler, total hours measure. This neatly demonstrates the tension between getting more information and getting accurate information.

The 2014 APS also made more effort to get information from reliable sources and, specifically, from payslips. The results supported the idea that employees tend to guess answers at focal points in the absence of any accurate information; non-compliance was much lower where documentation was consulted (see Table 4, above).

Owing to the re-structuring of the survey, only 8% of apprentices in 2014 APS report an hourly rate. These observations also show the lowest rates of non-compliance (although note that the actual rate derived by dividing pay by hours worked gives a high non-compliance rate, implying that the hourly rate is not always being received). They are however close to the rates reported for those who do not report and hourly pay but have both hours and pay taken from their payslip. This supports the findings from ASHE and LFS that stated rates are more accurate than undocumented estimates of wages and hours.

To investigate this issue, Drew et al (2016) carried out a qualitative analysis, interviewing apprentices, trainers and employers. This showed that, as far as the apprentices are concerned, 'hours of work' is at best a poorly understood concept; this was partly driven by the fact that what mattered was total take-home pay, not the hourly rate. Apprentices saw low wages during training as 'serving one's time'; they also assumed that employers were paying the correct wages. Hence, documentation is key to getting accurate information from apprentices. As noted above, it may explain the difference between the ASHE and APS estimates.

ASHE should not suffer from the hours/wages problem: it simply asks the employer to record total paid-for hours. However, the question could be misinterpreted, and it could be that ASHE respondents are omitting training hours to keep pay above the minimum. Drew et al (2015b) investigate this by comparing hours of apprentices and other employees, and concluded that there was no systematic difference; if firms are under-reporting hours, it does not seem to be significant.

In summary, a large part of the initial non-compliance identified amongst apprentices appears to be a result of poor data quality, and possibly a naïve interpretation of the data when aggregate statistics are presented. Using the information on how the data was collected has shown that the data problems are psychologically plausible and indirectly supported. Interestingly, a

response to the problem has been to accept that a quest for detail had a negative effect on data collection generally. This is the low pay Heisenberg problem: we are now more confident about the level of non-compliance, but have less information on precisely where it arises.

5.3 Processing

A third problem with the APS 2011 and 2012 was the error-checking. Each reported wage had a check value: if the reported wage was less than that, then the interviewer would get the interviewee to confirm results. For the 2011 APS the hourly-paid check was set at the NMWAR for that year, £2.50 per hour. Unfortunately, this was retained in 2012, although the NMWAR had increased. Moreover, the “50p” focal points are extremely popular when guessing responses, with a third of LFS respondents reporting wages that are multiples of 50p (Fry and Ritchie, 2013, Table 12). Thus, in the 2012 APS, many users reported a wage of £2.50, but it was impossible to tell if these were:

- Accurate and legitimate, as the pay period was the September before the new NMW came in.
- Accurate and unlawful, as the pay period was actually October or November.
- Inaccurate reporting by someone being paid at or above the NMWAR.
- Inaccurate reporting by someone being paid something below the NMWAR.

However, this was not picked up in initial processing. This single mass point thus contributed significantly to the incredibly high non-compliance initially reported.

In ASHE, one element of processing was discovered late. The research team, in line with the LPC, rounded wage calculations to the nearest penny. However, it was noted that there were a small but significant number of apprentices being paid one penny below the NMWAR. All of these individuals were monthly paid, all had calculated hours, and all had a stated hourly wage equal to the NMWAR.

Hourly pay in ASHE is calculated by dividing weekly basic earnings by weekly basic hours. For the monthly paid, these weekly figures are calculated from the supplied monthly figures. Hours are often specified on a weekly basis, even if salaries are monthly, in which case respondents are asked to multiply weekly hours by 4.348 to get a monthly total. Respondents are also required to convert decimal times (e.g. 37.5 hours) into hours and minutes (37 hours, 30 minutes). Clearly, there is much scope for error here, particularly as the ASHE questionnaire boxes only have space for two decimal places.

It seems plausible that the multiple calculations (from weekly hours and monthly pay to actual monthly wage; then wages and hours as reported to ASHE; ONS’ calculation of a weekly wage, and then an hourly one), were the cause of the under-payment. The numbers are small but sufficient to materially affect compliance rates: Table 6 shows the effect of allowing 1p below the NMW to be included as ‘compliant’.

Table 7 Non-compliance in ASHE allowing for rounding

	2013		2014	
	Non-compliant	Allowing for rounding	Non-compliant	Allowing for rounding
Wages based on hours x rate	7%	5%	8%	5%
Wages weekly or monthly	6%	5%	7%	6%
Overall	7%	5%	8%	5%

Source: ASHE 2013 and 2014, authors’ calculations, unweighted

This problem had not occurred in analyses of non-compliance before, as further investigation showed that it was almost entirely limited to apprentices (for other minimum wage

categories, rounding leads to higher wages; for apprentices there is very little rounding up). The reasons for this are not entirely clear. The best explanation seems to be that the very low level of the NMWAR provides more scope for rounding errors. This cannot be fully investigated though, as the other NMWs have never been as low as the NMWAR.

5.4 Weighting

Weighting the APS is relatively uncontroversial, as it is felt to be representative of the population.

In contrast, weighting the ASHE apprentice data is quite problematic. ASHE has weights to produce population estimates, and an additional set of weights calculated specifically for low pay work to address the expected non-response discussed above. As noted above, ASHE is only identifying less than a half of the expected apprentices, and there are reasons to believe that the missing observations are non-random (this is why we use the unweighted data in this paper). Therefore, the weighted ASHE estimates can be taken, at best, as a lower estimate of non-compliance for the general workforce.

5.5 Calculation of the non-compliance rate

One aspect that is simplified for the apprentice data is calculation of the non-compliance rate. First “the proportion of apprentices paid below the statutory minimum” does not suffer for the same relevance problems as “the proportion of all workers paid below the statutory minimum” where ‘all workers’ includes bankers and footballers. Second, as apprentices tend to be very low paid, there is little to be gained from defining a special “low-paid apprentice” category.

It is possible to create indices as described in section 4.5 for Apprentice Pay, using ASHE data. However, as apprentice pay is only available for three years, the numbers are small, and the data appears to show the same pattern for all years, these are of limited value at present.

5.6 Inferences

Drawing inferences from the apprentice pay data is also somewhat easier. For example, the much lower non-compliance rate for first-year apprentices is found in all breakdowns of the data, whether univariate or multivariate, and whether ASHE or APS is used (see Drew et al 2015b, 2016). While statistical data cannot prove any particular explanation, this is strong evidence that the change in the rate in the second year of the apprenticeship is causing problems. The fact that it appears in both the employer and employee data is also strong evidence that it represents genuine non-compliance in wages paid, and not misreporting. Of course, we still cannot distinguish between whether such non-compliance is deliberate or caused by the employer’s mistake. To resolve this, more qualitative evidence is needed.

5.7 Summary

Broadly, the measurement of non-compliance amongst apprentices can be summarised:

- A clearly defined population simplified analysis
- External information provided good evidence that ASHE under-samples
- Collecting detailed information was inconsistent with collecting accurate information
- A detailed study of the distributions was needed to uncover problems in both ASHE and APS
- Processing rules affected the outcome
- Interrogation of the data collection instrument helped understand problems, such as the concentration of response at £2.50 in 2012 APS
- Having both APS and ASHE allowed common features and differences to be identified

6. Conclusions

Minimum wages are part of the social and economic landscape in an increasing number of countries. Measuring and understanding compliance with minimum wages is important: for the success of the policy to be evaluated, and for enforcement to be effectively targeted.

This paper has reviewed statistical aspects of the measurement of non-compliance, and considered it in the specific context of the UK. Many papers talk about ‘measurement error’, but we have demonstrated that this can be composed of many elements:

- Inappropriate samples or population estimates
- Timing
- Interpretation of questions
- Ability to answer accurately
- Willingness to answer honestly
- Errors introduced by data processing

In principle, all but the last of these is well understood and considered by good analysts. It is a natural reaction to apply statistical tools to evaluate the statistical properties of the data. In practice, this paper has shown that properly addressing these matters requires an extensive technical knowledge of the data and processes, coupled with a considerable amount of detective work.

In the context of non-compliance, it is relatively easy to demonstrate the importance of knowledge of the data: the yes-no nature of non-compliance means that small inaccuracies can have very large effects. However, there is also a more general lesson here, as the fact that problems are less obvious does not necessarily mean that they should be ignored.

Consider, for example, the case of the UK LFS. Comments about its inaccuracy due to measurement errors have been circulating for years. But starting with the initial work on the effect of rounding of wages by employees on non-compliance rates (Ormerod and Ritchie, 2007), we now have a good understanding of exactly how and why some of that inaccuracy or uncertainty occurs, as well as recommendations for dealing with it (Ritchie et al, 2014; le Roux et al, 2013; LPC, 2015).

This deeper understanding also helps in determining responses to statistical findings. For example, the training hours questions in the APS just seemed to add to confusion; realising this led the APS redesign team to consider that these questions needed to be simplified, not complicated, even if that meant missing out on potential useful information.

Problems such as those connected with the training hours questions are amenable to survey redesign. On the other hand, factors such as human preferences for round numbers are harder to deal with. Nevertheless, a good understanding may allow one to develop mitigating strategies. For example, le Roux et al (2013) developed a ‘correction’ for rounding and applied it to their analyses; and Ritchie et al (2014) suggested that measurement error was only relevant for univariate statistics, and could be treated as a random error factor in multivariate models.

The analysis of non-compliance has also thrown the value of triangulation into sharp relief. Glamlich et al (1976) compared findings from employer and employee data forty years ago. In our analysis of apprentice pay non-compliance, the ability to compare two very different surveys has been invaluable.

As well as quantitative triangulation, qualitative data collection has been an important part of understanding the statistical data processes, from studying websites and shadowing interviewers, to formal qualitative studies such as that of Drew et al (2016). One of the most interesting things about the LPC’s research programme is the qualitative research stream: commissioned formal qualitative studies are complemented by a rolling programme of visits to workplaces, training organisations, support services and policy planners. The results of this programme are fully integrated into the LPC reports, and these have been invaluable in guiding statistical analysis to find weak points in the data.

As government organisations move towards greater use of administrative sources, understanding the characteristics of those data sources becomes harder. Perhaps the lesson of the work on non-compliance with the NMW is that the best way to learn about the data is to find an important binary question, which is more sensitive to errors.

References

- Ashenfelter, Orley, and Robert S. Smith. 1979. "Compliance with the Minimum Wage Law". *Journal of Political Economy* 87 (2). University of Chicago Press: 333–50.
- Basu, A. K., Chau, N. H., & Kanbur, R. (2010). Turning a Blind Eye: Costly Enforcement, Credible Commitment and Minimum Wage Laws. *The Economic Journal*, 120(543), 244-269.
- Belman D. and Wolfson P. (2013) *What does the minimum wage do?* Kalamazoo: Upjohn Institute
- Bewley, D. H., Wilkinson, D., & Rincon-Aznar, A. (2014). *An Assessment of the Changing Use of Flexible Employment and Implications for the National Minimum Wage, including Compliance* (No. 11815). National Institute of Economic and Social Research.
- Bhorat, H., Kanbur, R., and Mayet, N. (2013). A Note on Measuring the Depth of Minimum Wage Violation. *Labour*, 27(2):192{197.
- Bhorat, H., Kanbur, R., & Stanwix, B. (2015). *Minimum Wages in Sub-Saharan Africa: A Primer* (No. 9204). IZA Discussion Papers.
- Croucher R and White G (2004), *Enforcing the Minimum Wage: The Experience of Workers and Employers*, Research Report for the Low Pay Commission
- Dickens, R. (2015). How are minimum wages set? *IZA World of Labor*.
- Dickens, R., Machin, S., & Manning, A. (1999). The effects of minimum wages on employment: Theory and evidence from Britain. *Journal of Labor Economics*, 17(1), 1-22.
- Dickens, R., & Manning, A. (2004). Has the national minimum wage reduced UK wage inequality? *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 167(4), 613-626.
- DLNZ (2010) *Minimum Wage Review 2010: Officials' Report*. Department of Labour, New Zealand <http://employment.govt.nz/er/pay/backgroundpapers/2010/minimum-wage-review-2010.pdf>
- Drew H., Ritchie F., and Veliziotis M. (2015a) *The measurement of apprentice pay: interim report*. London: Low Pay Commission
- Drew H., Ritchie F., and Veliziotis M. (2015b) *The measurement of apprentice pay: final report*. London: Low Pay Commission
- Fry S and Ritchie F (2013) *Behavioural aspects of the National Minimum Wage*. Final report for the Low Pay Commission.
- Garnero, A., Kampelmann, S., & Rycx, F. (2015a). "Minimum wage systems and earnings inequalities: Does institutional diversity matter?" *European Journal of Industrial Relations*, v21(2) pp115–130
- Garnero, A., Kampelmann, S., & Rycx, F. (2015b) "Sharp Teeth or Empty Mouths? European Institutional Diversity and the Sector-Level Minimum Wage Bite". *British Journal of Industrial Relations* doi: 10.1111/bjir.12104 53:4 December pp. 760–788
- Gramlich, E., Flanagan R., and Wachter M. (1976) "Impact of minimum wages on other wages, employment, and family incomes." *Brookings Papers on Economic Activity*, 409-461.
- Griffiths C, Ormerod C and Ritchie F (2007) *Measuring low pay: Measures and precision*. <http://www.ons.gov.uk/ons/guide-method/method-quality/specific/labour-market/annual-survey-of-hours-and-earnings/low-pay-estimates/measuring-low-pay---measures-and-precision.pdf>
- Ham, A. (2015). *Minimum wage violations in a dual labor market with multiple floors*. Available at SSRN 2557635.
- Hicks S, Conn S and Johnson J (2009), 'Characteristics of those paid below the National Minimum Wage', *Economic & Labour Market Review*, vol. 3, no. 1, pp. 67–73
- Higton, J. (2013). *Apprenticeship pay survey 2012: research findings*. Department for Business and Skills (BIS). October 2013. BIS Research Paper 121.
- Higton J., Kaur-Ballagan K., Navin Shah J., and Medien K. (2012) *Apprentice Pay Survey 2011*. Department for Business and Skills (BIS). October 2013. BIS Research Paper 64.
- IPSOS-MORI (2012) *Non-compliance with the National Minimum Wage*. Research for the Low Pay Commission. February.

- Kampelmann, S., Garnero, A., & Rycx, F. (2013). *Minimum wages in Europe: does the diversity of systems lead to a diversity of outcomes?* ETUI, European Trade Union Institute.
- Kennan, J. (1995). The elusive effects of minimum wages. *Journal of Economic Literature*, 1950-1965.
- Knight J. (2010) *Data sources and concepts explained*. Low Pay Commission report.
- LPC (2000) *Low Pay Commission Second Report*. London: Low Pay Commission
- LPC (2015) *National Minimum Wage Report 2015*. London: Low Pay Commission
- Metcalf, D. (2007). *Why has the British national minimum wage had little or no impact on employment?* Centre for Economic Performance Discussion Paper no. 781, London School of Economics
- Metcalf, D. (2008). Why has the British national minimum wage had little or no impact on employment? *Journal of Industrial Relations*, 50(3), 489-512
- Milton J (2004), 'New methodology for low pay estimates'. <http://www.ons.gov.uk/ons/guide-method/method-quality/specific/labour-market/annual-survey-of-hours-and-earnings/low-pay-estimates/new-methodology-for-low-pay-estimates-in-2004.pdf>
- Nelms L., Nicholson P. and Wheatley T. (2011) *Employees earning below the Federal Minimum Wage: Review of data, characteristics and potential explanatory factors*. Minimum Wages and Research Branch—Fair Work Australia
- Osborne G. (2015) *Summer Budget Speech*. 8th July. <https://www.gov.uk/government/speeches/chancellor-george-osbornes-summer-budget-2015-speech>
- OECD (2015) *Minimum wages after the crisis: making them pay*. OECD Directorate for Employment, Labour and Social Affairs. May. <http://www.oecd.org/social/Focus-on-Minimum-Wages-after-the-crisis-2015.pdf>
- Ormerod C and Ritchie F (2007) 'Issues in the Measurement of Low Pay', *Economic and Labour Market Review*, Volume 1, No. 6, pp.37-45.
- Randolph G. and Panknin K., eds (2015) *Global Wage Debates: Politics or economics?*. JustJobsNetwork. September.
- Rani, U., Belser, P., Oelz, M., & Ranjbar, S. (2013). Minimum wage coverage and compliance in developing countries. *International Labour Review*, 152(3-4), 381-410.
- Ritchie F., Whittard D. and Dawson C. (2014) *Understanding official data sources: final report*. London: Low Pay Commission
- le Roux S., Lucchino P. and Wilkinson D. (2013) *An investigation into the extent of non-compliance with the national minimum wage*. Report for the Low Pay Commission, London.
- Strobl, E., & Walsh, F. (2003). Minimum Wages and Compliance: The Case of Trinidad and Tobago*. *Economic Development and Cultural Change*, 51(2), 427-450.
- Weil, D. (2005). Public enforcement/private monitoring: Evaluating a new approach to regulating the minimum wage. *Industrial & Labor Relations Review*, 58(2), 238-257.
- Wilkinson D., Le Roux S., and Lucchino P. (2012) *An investigation into the extent of non-compliance with the NMW*, presentation to LPC Non-technical Workshop, October
- Winterbotham M., Davies B., Murphy L., Huntley Hewitt J., and Tweddle M. (2014) *Apprentice Pay Survey 2014*. BIS Research Paper no 207. Department for Business, Innovation and Skills.
- Yamada, H. (2012). Non-compliance with the Minimum Wage Law when Completely New Minimum Wage Laws Are Established: The Case of South Africa. *African Development Review*, 24(1), 41-51.
- Ye, L., Gindling, T. H., & Li, S. (2015). Compliance with legal minimum wages and overtime pay regulations in China. *IZA Journal of Labor & Development*, 4(1), 1-35.

Recent UWE Economics Papers

See <http://www1.uwe.ac.uk/bl/research/bristoleconomicanalysis> for a full list.

2016

- 1608 **Measuring compliance with minimum wages**
Felix Ritchie, Michail Veliziotis, Hilary Drew and Damian Whittard
- 1607 **Can a change in attitudes improve effective access to administrative data for research?**
Felix Ritchie
- 1606 **Application of ethical concerns for the natural environment into business design: a novel business model framework**
Peter Bradley, Glenn Parry and Nicholas O'Regan
- 1605 **Refining the application of the FLQ Formula for estimating regional input coefficients: an empirical study for South Korean regions**
Anthony T. Flegg and Timo Tohmo
- 1604 **Higher education in Uzbekistan: reforms and the changing landscape since independence**
Kobil Ruziev and Davron Rustamov
- 1603 **Circular economy**
Peter Bradley
- 1602 **Do shadow banks create money? 'Financialisation' and the monetary circuit**
Jo Michell
- 1601 **Five Safes: designing data access for research**
Tanvi Desai, Felix Ritchie and Richard Welpton

2015

- 1509 **Debt cycles, instability and fiscal rules: a Godley-Minsky model**
Yannis Dafermos
- 1508 **Evaluating the FLQ and AFLQ formulae for estimating regional input coefficients: empirical evidence for the province of Córdoba, Argentina**
Anthony T. Flegg, Leonardo J. Mastronardi and Carlos A. Romero
- 1507 **Effects of preferential trade agreements in the presence of zero trade flows: the cases of China and India**
Rahul Sen, Sadhana Srivastava and Don J Webber
- 1506 **Using CHARM to adjust for cross-hauling: the case of the Province of Hubei, China**
Anthony T. Flegg, Yongming Huang and Timo Tohmo
- 1505 **University entrepreneurship education experiences: enhancing the entrepreneurial ecosystems in a UK city-region**
Fumi Kitagawa, Don J. Webber, Anthony Plumridge and Susan Robertson
- 1504 **Can indeterminacy and self-fulfilling expectations help explain international business cycles?**
Stephen McKnight and Laura Povoledo
- 1503 **User-focused threat identification for anonymised microdata**
Hans-Peter Hafner, Felix Ritchie and Rainer Lenz
- 1502 **Reflections on the one-minute paper**
Damian Whittard

1501 **Principles- versus rules-based output statistical disclosure control in remote access environments**
Felix Ritchie and Mark Elliot

2014

1413 **Addressing the human factor in data access: incentive compatibility, legitimacy and cost-effectiveness in public data resources**
Felix Ritchie and Richard Welpton

1412 **Resistance to change in government: risk, inertia and incentives**
Felix Ritchie

1411 **Emigration, remittances and corruption experience of those staying behind**
Artjoms Ivlevs and Roswitha M. King

1410 **Operationalising 'safe statistics': the case of linear regression**
Felix Ritchie

1409 **Is temporary employment a cause or consequence of poor mental health?**
Chris Dawson, Michail Veliziotis, Gail Pacheco and Don J Webber

1408 **Regional productivity in a multi-speed Europe**
Don J. Webber, Min Hua Jen and Eoin O'Leary

1407 **Assimilation of the migrant work ethic**
Chris Dawson, Michail Veliziotis, Benjamin Hopkins

1406 **Empirical evidence on the use of the FLQ formula for regionalizing national input-output tables: the case of the Province of Córdoba, Argentina**
Anthony T. Flegg, Leonardo J. Mastronardi and Carlos A. Romero

1405 **Can the one minute paper breathe life back into the economics lecture?**
Damian Whittard

1404 **The role of social norms in incentivising energy reduction in organisations**
Peter Bradley, Matthew Leach and Shane Fudge

1403 **How do knowledge brokers work? The case of WERS**
Hilary Drew, Felix Ritchie and Anna King

1402 **Happy moves? Assessing the impact of subjective well-being on the emigration decision**
Artjoms Ivlevs

1401 **Communist party membership and bribe paying in transitional economies**
Timothy Hinks and Artjoms Ivlevs

2013

1315 **Global economic crisis and corruption experience: Evidence from transition economies**
Artjoms Ivlevs and Timothy Hinks

1314 **A two-state Markov-switching distinctive conditional variance application for tanker freight returns**
Wessam Abouarghoub, Iris Biefang-Frisancho Mariscal and Peter Howells

1313 **Measuring the level of risk exposure in tanker shipping freight markets**
Wessam Abouarghoub and Iris Biefang-Frisancho Mariscal

1312 **Modelling the sectoral allocation of labour in open economy models**
Laura Povoledo

