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Minimum wages and wage inequality in New Zealand

Dean R. Hyslop, David C. Maré and Lily Stelling

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Author contact details

Dean R. Hyslop
Motu Economic and Public Policy Research
PO Box 24390
Wellington 6142, New Zealand
E-mail: dean.hyslop@motu.org.nz

David C. Maré
Motu Economic and Public Policy Research
PO Box 24390
Wellington 6142, New Zealand
E-mail: dave.mare@motu.org.nz

Lily Stelling
University of Queensland
Brisbane, Australia
E-mail: uqlstell@uq.edu.au

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Motu Economic and Public Policy Research

PO Box 24390
Wellington
New Zealand

info@motu.org.nz
www.motu.org.nz

+64 4 9394250

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Abstract

This paper addresses the effects of dramatic increases in minimum wages on wage inequality in New Zealand since 2000. Over this period the adult minimum wage increased more than 75% in CPI-adjusted real terms, and applicable minimum wages for teenagers increased by more than 200%. There has been broad-based wage growth across the distribution, with remarkably stable growth of about 30% (1.2% per annum) across the top-half of the wage distribution, and substantially stronger at lower quantiles (up to 66% at the 5th percentile). This has compressed the lower tail, and reduced wage inequality: between 1997-2000 and 2020-2023, the standard deviation of log(wages) fell by 16%, while the log-difference between the 50th and 10th percentiles of wages (50-10 gap) fell by 28% compared to a small (4%) increase in the 90-50 gap. Adapting the DiNardo, Fortin and Lemieux (1996) methodology to assess the contributions of changes in worker characteristics, economic (wage) returns to characteristics and the minimum wage to changes in wage inequality over this period, we conclude that minimum wage increases explain most of the reduction in wage inequality (about 90% of the 50-10 change, and 70% of the change in the standard deviation of log(wages)), while changes in worker characteristics modestly increased wages and inequality, and changes in returns reduced inequality slightly. However, there has been an unexplained increase in the density between the recent minimum and median wages: differences between male and female wage changes are consistent with recent pay equity settlements being a contributing factor, together with minimum wage spillover effects.

JEL codes

J31, J38

Keywords

Minimum wages, wage distribution, wage inequality, spillovers

Summary haiku

Large increases in

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1 Introduction

There has been a substantial revival in minimum wage policies internationally in recent decades. This includes the introduction of minimum wages (e.g. in the UK in the late 1990s, and Germany in 2015), as well as systematic increases in the national minimum wage levels (e.g. large increases in the minimum wage in Hungary in 2001; and increases associated with the National Living Wage in the UK in 2016, with the goal of reaching two-thirds of the median wage by 2024), and the introduction or increases in state, county or city level minimum wages in the US. Although most minimum wage research continues to focus on the issue of dis-employment effects the consensus in the literature is that employment effects are quite small.[1] In contrast, minimum wages can have noticeable effects on the wage distribution and are generally negatively correlated with the degree of wage inequality (Autor, Manning, and Smith 2016; Bossler and Schank 2023; Butcher, Dickens, and Manning 2012; DiNardo, Fortin, and Lemieux 1996; Fortin, Lemieux, and Lloyd 2021; Lee 1999).

In this paper we analyse the effects of substantial increases in New Zealand's minimum wage since 2000 on (hourly) wage inequality. New Zealand is a particularly interesting case in point for at least three reasons. First, New Zealand had a comparatively high minimum wage in 2000 internationally: New Zealand's (median) Kaitz index ranked 7th in the OECD at just over 50% (OECD 2025).[2] Second, between 2000 and 2023, New Zealand's minimum wage increased more than 75% in CPI-adjusted real terms, while the Kaitz index increased 16 percentage points (32%).[3] The increases largely occurred in two tranches, associated with Labour-led coalition governments until 2008, and from 2017 to 2023. Despite the comparatively high minimum wage, New Zealand ranks lower (9th) and close to the OECD average in terms of the estimated fraction of workers earning at or below the minimum wage (OECD 2022), suggesting a

[1] Neumark and Shirley (2022) estimate a median elasticity of -0.12, and Wolfson and Belman (2019) and Martínez and Martínez (2021) report a central range of -0.07 to -0.13, which are towards the lower end of the [-0.1,-0.3] range reported by Brown (1999). Adjusting the employment elasticity for the elasticity of affected workers' average wage with respect to the minimum wage to focus on the own-wage elasticity (OWE), Dube (2019) and Dube and Zipper's (2024) estimate median OWEs of -0.16 and -0.13 respectively. A variety of research has also examined other effects of minimum wages, including increased productivity (Coviello, Deserranno, and Persico 2018; Papps 2012; Riley and Bondibene 2017; Dustmann et al. 2019); reduced turnover (Brochu and Green 2013; Dube, Lester, and Reich 2016; Dickson and Papps 2016); higher prices (Allegretto and Reich 2018); and reduced profits (Bell and Machin 2018).

[2] The median (mean) Kaitz index measures the minimum wage as a fraction of the median (mean) wage (Kaitz 1970), and is a commonly used metric to compare minimum wage levels across countries and jurisdictions.

[3] The relative increase in the Kaitz index ranked 9th among OECD countries (OECD 2025). The increases resulted in New Zealand having the 6th highest Kaitz index in 2023, and overtaken only by Portugal and Mexico with higher relative increases (Mexico since 2005). New Zealand is also the highest ranked OECD country in terms of the minimum wage contribution to labour costs and net household income for single full-time, full-year 40 year-old workers (OECD 2022).

comparatively compressed lower tail of the wage distribution.[4] Third, reforms during the 2000s eliminated the youth minimum wage that had applied to 16-19 year-olds (at 60% of the adult minimum wage until 2001): together with the adult minimum wage increases, these changes resulted in substantially larger increases in the applicable minimum wage for youth workers.[5] Finally, there has been little analysis of wage inequality in New Zealand.[6]

The analysis uses data from the Household Labour Force Survey (HLFS) and HLFS (Income) supplement (HLFS-IS), which has collected wage, earnings and income information from June-quarter HLFS recipients annually since 1997.[7] We begin by documenting trends over time in various measures related to the increasing minimum wage and wage inequality. These include the (CPI-adjusted) real value of the minimum wage, the average wage and quantiles of the wage distribution; commonly used measures of the "bite" of the minimum wage, including the Kaitz index, the fraction of workers earnings less than or equal to the current minimum, and the fraction earning less than the next minimum wage; and alternative measures of wage inequality, including log(wage) quantile differences, and the standard deviation of log(wages). As the increases in applicable minimum wages were much greater for teenagers, and youth workers are generally more affected by the minimum wage, we separately document the patterns for youth (16-25 year-olds) and adult (25+ years) workers. In addition, we document comparative wage and inequality trends for male and female workers, partly because minimum wages tend to affect female wages more than males and more specifically because of recent pay equity settlements that have predominantly affected female workers.

First, we show that there has been steady wage growth across the distribution, with noticeably stronger growth in the lower tail of the distribution. In particular, wage growth from 2000 to 2023 across the top half of the distribution was remarkably stable, between 31-33% (about 1.2% annually) measured at the 50th (median), 75th, 90th and 95th percentiles. In contrast, wages at the 25th, 10th, and 5th percentiles increased 39%, 47% and 66% respectively. Second, the fraction of workers with wages less than or equal to the minimum wage increased from 3-4% before 2000 to 10% in 2008, and has remained in the 8-10% range since then. As a result,

[4] New Zealand appears to have relatively low wage inequality compared to other OECD countries. For example, since 2000 the variance of log(wages) has been around 0.2 (and the 90-10 gap around 1) and falling. These measures are higher than Sweden and Italy, similar to France, Germany and Norway, and lower than the UK, Japan, Canada and the US (OECD 2021).
[5] There are exemptions from the minimum wage for workers with a disability that significantly affects their ability to do the work, which requires an exemption permit. There are also sub-minimum wage rates, set at 80% of the adult rate, for workers undertaking recognised workplace training (since 2003), and new youth workers (since 2008). Hyslop and Stillman (2021) document that there is relatively little evidence that the sub-minimum exemptions are used.
[6] Most analysis of labour market effects on inequality have focused on weekly or annual earnings (e.g. Hyslop and Yahanpath 2006) or household incomes (e.g. Hyslop and Maré 2005; Maloney and Pacheco 2012).
[7] The HLFS-IS has previously been referred to as the New Zealand Income Survey (NZIS).

wages at the 5th percentile increased roughly in line with the minimum wage over the period, while the 10th percentile has increased with the minimum wage since 2008. This fraction has remained stable, while the minimum wage and the fraction of wages below the next minimum increased (particularly after 2017), which suggests the minimum wage may be creating spillover effects on wages above the minimum. Third, the quantile wage changes imply relatively steady upper tail inequality, and declining lower tail inequality: e.g. the relative difference between the 90th and 50th percentile (90-50) of wages increased 2% (1.4 percentage points, ppt) from 2000 to 2023, while the 50-10 difference fell 26% (11.4 ppt). As a broader measure of wage inequality, the standard deviation of log(wages) also fell 14% (6.6 ppt) over this period.

The trends for youth workers are noticeably stronger than for adults. For example, the fraction of youth affected by the minimum wage increased from 3-5% before 2000 to almost 30% by 2008 and has fluctuated between 20-30% since then. The stronger bite of the minimum wage on youth workers has translated through to youth wages at the 10th and 25th percentiles increasing with the minimum wage since 2008, and relatively stronger lower tail increases than for all workers. As the minimum wage has gradually converged toward the median wage for youth, the growth in the youth median wage has been stronger (39%) than for adults. Curiously, however, the upper tail wage growth for youth has been relatively weak (e.g. 19% and 17% at the 90th and 95th percentiles, compared to over 30% for adults). These changes imply stronger declines in youth wage inequality: the 50-10 difference has declined steadily since 2000, with a sharp drop in 2008 (74% total decline since 2000); while the 90-50 difference and the standard deviation of log(wages) have also declined steadily (34% and 40% respectively since 2000).

The trends in male and female wages have been similar. However, female wages have increased faster than male wages across the distribution: e.g. median wages increased 6% more for females than males over the period. In addition, wage inequality is lower for female than male workers and has fallen slightly more in relative terms.

We then turn our attention to modelling the effects of the minimum wage on the wage distribution and wage inequality. To do this, we adapt the methodology introduced by DiNardo, Fortin and Lemieux (1996) (DFL) to model the effects of minimum wages and other factors on the wage distribution. We analyse wage changes using two steps. First, we pool years to get larger samples and use kernel density methods to estimate the wage distributions the start (1997-2000) and end of the period (2020-2023). Second, we create hypothetical wage distributions to consider how the distribution was affected by minimum wage increases and other changes in other factors. While our primary focus is the effect of changes in the level of the adult minimum wage, we also account for other factors that could influence the wage distribution: in particular, changes in workers' observable characteristics (sociodemographic, location, etc.); and changes in returns to these characteristics, and overall wage growth. DFL's approach to modelling the effects of minimum wages assumes no spillover effects on wages above the minimum, and involves replacing the lower tail (below the minimum wage) of the wage distribution when the minimum wage was low with the corresponding tail of the wage distribution when the minimum wage was high. To investigate the importance of spillovers, we also adapt the recent regression-distribution approach of Fortin, Lemieux and Lloyd (2021), and use the results to help guide our analysis of spillover effects.

This analysis first shows that changes in workers' characteristics over the period acted to increase wages and <u>increase</u> wage inequality over the period. Second, we estimate that changes in the relative returns to characteristics reduced inequality slightly, partially counterbalancing the increasing effect of the change in characteristics. Together, these two factors provide a good fit to the change in the upper tail of the distribution over time: the first is consistent with the changing characteristics representing an increase in human capital of workers, while the second suggests the changes in returns were relatively stronger for workers with lower human capital. Third, controlling for these two sets of factors, we show that the minimum wage changes substantially reduced wage inequality over the period. The direct effects of the minimum wage changes account for about 90% of the fall in lower tail (50-10) wage inequality, and 70% of the fall in the standard deviation of log(wages).

There remains a noticeable unexplained increase in wage density between the current minimum and median wages. Separate analyses of male and female changes show a greater increase in wage density in this region, and relatively more of the increase is accounted for by changes in returns, for female than male workers. This is in line with expected effects of pay equity settlements, although it provides only a partial account of the unexplained changes. In addition, we find some evidence of spillovers on wages up to 10-15% above the minimum in the latter part of the period. Allowing for such spillovers accounts for some of the density increase between the minimum and median wages, and accounts for about 20% of the fall in each of the 50-10 and standard deviation inequality measures.

The remainder of the paper is organised as follows. In the next section we discuss the expected effects of a binding minimum wage on the distribution of wages and wage inequality, and review relevant literature. In section 3 we discuss the data used in the analysis, and summarise trends in minimum wages, wages and wage inequality. Section 4 contains the main analysis of our estimated effects of minimum wages on the wage distribution and wage inequality, following which the paper concludes with a discussion.

2 Theory and literature review

We begin with a brief discussion of the theoretical effects of a minimum wage on the wage distribution. At one extreme, the standard neoclassical perfectly competitive model has the sharp prediction that all workers earning less than the minimum wage will lose their jobs. This implies the wage distribution will simply be truncated below the minimum wage. As a result of the implied systematic employment loss of low wage workers, the introduction or increase in the minimum wage will reduce wage inequality conditional on employment (i.e. among the remaining employed workers) but, treating unemployed workers as having zero wages, will increase unconditional wage inequality.

In general, deviations from the neoclassical competitive model are expected to result in less (if any) employment loss. At the other extreme of a static monopsonistic labour market, consider the introduction of a minimum wage above the monopsony wage and below the competitive wage (equal to a worker’s marginal productive). In this model the wages of workers below the minimum will increase to the minimum wage, and the employment of such workers will also increase; it will have no effect on other workers. As a result, the wage distribution will be censored below the minimum wage, with a spike at the minimum due to the increase in wages of previously sub-minimum workers and the increase in such workers; and there will be a proportional drop in the density of wages above the minimum associated with that employment increase. Raising the wages of existing low wage workers will reduce wage inequality, while any increase in employment among low wage workers will increase inequality.

The commonly observed spike in wage distributions at the minimum wage (DiNardo, Fortin, and Lemieux 1996; Maré and Hyslop 2021) implies the competitive model inadequately captures the existence of frictions in the labour market. In addition, neither of these extreme models predicts any effect on the wages of workers earning above the minimum wage.[8] Models that include such spillover effects include Grossman (1983), based on efficiency wages and an increase in demand for non-minimum wage workers; Flinn (2006; 2010), in which workers bargain over the wage; and Butcher, Dickens and Manning (2012), based on a wage posting

[8] Brown’s (1999) extensive review of minimum wages concludes there is tentative evidence that spillovers exist but that they do not extend far above the minimum. More recent US evidence tends to find more compelling evidence of spillovers (Autor, Manning, and Smith 2016; Fortin, Lemieux, and Lloyd 2021; Lee 1999).

model in which employers determine the wage offered to workers. Any minimum wage spillover effects will further compress the wage distribution and reduce wage inequality.

Abstracting from any monopsony-related effects, Figure 1 provides a stylised description of possible minimum wage effects on the wage distribution.[9] The dashed line presents a simple normal counterfactual distribution for log(wages) in the absence of minimum wages, with mean 3.5 and standard deviation 0.5, which approximate the empirical values of current wages in New Zealand. The solid line shows the actual distribution in the presence of a minimum wage (log(minimum wage)=3.0), assuming no employment loss, 75% compliance for wages below the minimum wage causing a density deficit in this region (the remaining 25% non-compliance includes exemptions and mis-measured wages), and the cumulative displacement of wages from below the minimum being distributed to a mass at the minimum wage (40%) and spillovers up to 20 log-points above the minimum wage.[10] The dotted line shows the actual wage distribution, assuming 20% employment loss of directly-affected workers (i.e. those with wages below the minimum wage): the density loss below the minimum wage will be distributed above the minimum (so that the distribution integrates to 1).

Figure 1 highlights four possible effects of the minimum wage. First, employment loss, that we assume is concentrated among directly affected workers, will present as a reduction in density below the minimum wage and an increase in density above the minimum wage. Second, the displacement of wage density from below the minimum associated with firms complying with the minimum wage: as the minimum wage binds on affected lower wages, there will be a reduction in the mass below the minimum. Third, a mass-point spike in the distribution at the minimum wage associated with wages being displaced from below. Fourth, spillover effects on wages above the minimum wage associated with maintaining wage relativities over the range around the minimum wage.

Any employment loss among affected lower wage workers is expected to increase <u>unconditional</u> wage inequality (i.e. including zero wages of displaced workers), but reduce wage inequality among those employed, as this compresses the observed wage distribution: any monopsony-related increase in employment will counterbalance this effect. Displacement effects that raise the wages of directly affected workers up to the minimum will also compress the wage distribution and lower inequality. Finally, any spillover effects on wages above the

[9] As discussed, monopsony would be expected to reduce any employment loss, resulting in more density mass at the minimum wage and a corresponding decrease in density above the minimum.

[10] Note, the spillover effects may include not directly affected workers' wages above the minimum wage being increased to maintain relativities with directly affected workers' wages.

minimum will further compress wages and reduce inequality, assuming spillovers do not reach far up the distribution (e.g. concentrated below the median wage).

2.1 Literature review of inequality effects of minimum wages

In an early attempt to include possible employment loss contributions to minimum wage effects on wages, Meyer and Wise (1983a; 1983b) relaxed the competitive model to analyse the effects of minimum wage on youth workers. They allowed both non-compliance and employment loss below the minimum wage, while assuming no spillover effects above the minimum wage. Among workers whose wages would be below the minimum wage in the absence of the minimum wage, they assumed that a fraction (p1) continues to be paid that wage (non-compliance) in the presence of the minimum wage, a fraction (p2) is paid the minimum wage, and the remaining fraction (1-(p1+p2)) lose their jobs. This will result in a reduction in the density below the minimum wage associated with compliance and employment loss; a spike at the minimum wage associated with compliance; and a proportional increase in the density above the minimum wage associated with employment loss of minimum wage affected workers: the latter will appear as a spillover effect in the distribution but is driven by the employment loss. Meyer and Wise estimated 4-6% youth employment loss associated with the minimum wage over 1973-78 in the US and, although the average wage of employed youth is higher, this increase is more than offset by the loss of wages of those not employed.

Dickens et al. (1998) explored the Meyer and Wise methodology in the UK context, and concluded that the results were very sensitive to functional form assumptions. More recently, Cengiz et al. (2019) analysed changes in the frequency distribution of wages around a minimum wage change to identify both employment effects and wage changes. They concluded that there was essentially no employment loss over five years following state-level minimum wage increases.

This result is in line with predominant results in the literature that the employment effects associated with minimum wages are typically small,[11] so that the employment impacts on the wage distribution are likely to be minor and difficult to identify. For this reason, most empirical research on minimum wages and wage inequality abstracts from employment effects, and focuses on the effects on the observed wage distribution.

[11] For example, Brown (1999) concluded the employment elasticity on affected workers was in the range of -0.1 to -0.3. More recently, Neumark and Shirley (2022) and Dube (2019) report median estimates of -0.12 and -0.16 respectively, while Wolfson and Belman (2019) and Martínez and Martínez (2021) both report a central range of -0.07 to -0.13.

Much of the US literature has focused on the contribution of declining minimum wages to rising wage inequality in the US since the 1980s. First, DiNardo et al. (1996) used kernel density methods to estimate wage distributions, and developed a semiparametric approach to construct counterfactual distributions to evaluate the effects of changes in various factors including minimum wages. Abstracting from possible spillover effects, they concluded that the decline in the minimum wage accounted for about two-thirds of the increase in males and female lower tail inequality (50-10 difference) between 1979 and 1988, and 25-30% of the increase in the standard deviation of log(wages). Lee (1999) extended this analysis to allow for possible spillover effects, and estimated that the declining minimum wage accounted for greater fractions of the rise in lower tail inequality (about 70% for men and 70-100% for women), and about half of the increase in the standard deviation of log(wages) over the same period.[12] Correcting potential bias associated with correlation between states' minimum and median wages in Lee's estimates, Teulings (2003) reached similar conclusions regarding the minimum wage contribution to inequality changes,[13] while Autor et al. (2016) found minimum wage declines explained smaller fractions (30-55%) of the increases in lower tail wage inequality in the 1980s. Finally, using a rich distribution-regression approach to estimate spillover effects on wages, Fortin et al. (2021) estimated spillover effects similar to those found by Lee (1999) for the 1980s: accounting for the spillovers, they concluded that the declining minimum wage explained most of the lower tail inequality increase in the 1980s. Fortin et al. (2021) also found that spillovers have been smaller since the 1990s, which helps explain the differences between Lee (1999) and Autor et al. (2016).

In contrast to the US literature, research from other jurisdictions has often been in the context of the introduction of, or increases in, minimum wages. UK research has focused on the National Minimum Wage (NMW) since its introduction in1999. Stewart (2012) analysed year-to-year wage changes to examine whether the NMW had spillover effects on wages. He found no evidence of spillover effects from its introduction until 2008 and, as the NMW was also below the 10th percentile of wages, inferred that the NMW did not affect the drop in the lower tail wage inequality (50-10 difference) since the mid-1990s. In contrast, incorporating lagged effects, Butcher et al. (2012) estimated significant spillover effects on wages (up to 40% above

[12] Lee (1999) noted that wage spillover effects will be overstated in the presence of (any) dis-employment effects. That is, removing sub-minimum wage workers from the distribution will raise the density of those earning at or above the minimum wage, thus generate apparent (spurious) spillovers on the observed wage distribution. Autor et al. (2016) also discussed this issue and argued that any spurious dis-employment spillover effects are expected to be trivial.

[13] However, Teulings (2003) argued that the minimum wage spillovers are due to a larger (non-linear) effect on the returns to human capital than Lee (1999) estimated.

the minimum), and estimated that the NMW accounted for about 40% of the drop in lower tail inequality (50-10 difference) from 1998 to 2010 for young workers; and smaller effects on more weakly declining inequality for older workers.

Similarly, Bossler and Schank (2023) analysed the effects of the 2015 introduction of a national minimum wage on wage inequality in Germany. German wage inequality increased strongly during the 2000s, before falling after 2010. Using DFL counterfactual constructions, they estimated that the minimum wage, which affected 10-14% of workers, can account for about half of the drop in inequality between 2014 and 2017. They also found little evidence of spillover effects above the minimum wage and concluded that any dis-employment effects were small.

Koeniger et al. (2007) investigate the impact of a range of labour market institutions on wage inequality across 11 OECD countries between 1973 and 1999.[14] They estimate log-linear regressions for the 90-10, 90-50 and 50-10 wage differentials on measures of these institutions and other controls. Although the main baseline results, which include country and year fixed effects, show that (relatively) higher minimum wages tend to compress the wage distribution, counterintuitively the compression is somewhat stronger on the upper- than the lower tail of the distribution.[15]

New Zealand research on the relationship between minimum wages and wage inequality is limited. Pacheco (2009) analysed the relationship separately for teenage versus adult workers in New Zealand between 1997 and 2007, during which time the adult minimum wage rose 29% in real value, and there were much larger increases for teenage workers. Wage inequality for adults increased slightly after 2000, while youth wage inequality decreased steadily from 1998. Regressing the 90-50 and 50-10 differences on the log(real minimum wage), Pacheco found that the minimum wage had small and insignificant effects on both tails of adult inequality, consistent with the minimum wage being relatively non-binding on adult workers through the period. In contrast, the minimum wage significantly reduced lower tail inequality (coefficient=–

[14] As well as measures of the minimum wage (measured by the ratio of the minimum to the median wage), the analysis includes variables for the level of employment protection, union density and coordination (the fraction of workers covered by collective agreements), the benefit replacement rate, (employment) tax rate, and the relative unemployment of skilled to unskilled workers. The 11 countries analysed are: Australia, Canada, Finland, France, Germany, Italy, Japan, the Netherlands, Sweden, the UK and the US.

[15] A 1 ppt increase in the minimum wage relative to the median is estimated to reduce the 90-10, 90-50 and 50-10 differences (statistically significantly) by -0.27, -0.15 and -0.12 ppt respectively. They also estimate the regression in first differences of pooled 3-year averages, with country and year fixed effects. The estimates from that specification show most of the wage compression associated with higher minimum wage changes is in the lower tail (-0.086 for the change in the 50-10, compared to -0.027 for the 90-50 change).

0.63) and had a small and insignificant effect on upper tail inequality for youth, suggesting the minimum wage changes were having some bite on teenage wages.

Rosenberg (2017) presents a descriptive analysis of changes in wage inequality from 1998-2015. He found that relative wage growth is U-shaped across the distribution, and was strongest in the lowest decile, which was most heavily affected by the minimum wage. However, given that "the more highly paid employees were, the faster their hourly wage rates increased, creating growing inequality … it is surprising that the minimum wage does not support a greater ripple effect up the wage scale" (p2, p4), he concluded any spillover effects were minor. In analysing contributions to income changes over the period 1998-2004, Hyslop and Yahanpath (2006) found that wage growth was fairly even across the lower tail of the (income) distribution, and stronger across the top half of the distribution, suggesting stable lower tail inequality and growing upper tail inequality during that period.

In addition to the statutory minimum wage, 2013 saw the introduction of a living wage set at $18.40 (36% above the minimum wage) by Living Wage Aotearoa New Zealand (LWANZ) (2025). The living wage has been periodically reviewed and increased, varying between 12% and 36% above the minimum wage. Compliance with the living wage is voluntary, but employers who satisfy various conditions can become accredited living wage employers with LWANZ: the number of accredited employers has grown gradually over time to more than 350 currently. The introduction of the living wage above the minimum wage and the increase in its visibility and support suggests it could play a role in the growth of workers paid above the minimum wage. Despite this, we find no discernible evidence of an increase in workers paid at or near the living wage in preliminary analysis: this may be because living wage accreditation is not binding on employers' wage decisions, or because any consequent effects may result in wages paid <u>above</u> rather than <u>at</u> the living wage. For this reason, we do not consider living wage effects in our analysis below.

Finally, since 2017 several pay equity settlements for groups of public sector workers have been agreed. These settlements cover low wage, and predominantly female, workers who earn at or near minimum wages. The first and largest of these settlements over the sample period was the Care and Support Workers Pay Equity Settlement, agreed by the government in 2017 (Ravenswood and Douglas 2022) and estimated to cost about $2 billion over five years (Minister for the Public Service 2024). This settlement raised the minimum wages of affected workers from the national minimum of $15.75 to a scale ranging from $19–$23.50 on 1 July 2017, with further increases over the following five years. Noy and Allan (2019) estimated that this increased earnings of affected workers by 7-14% in the first year of the settlement, which will otherwise appear as a minimum wage spillover effect on wages.

3 Data and descriptive trends

3.1 Data description

The analysis uses data from Statistics New Zealand's (SNZ) Household Labour Force Survey (HLFS) and its annual Income Supplement (IS) from 1997 until 2023. These data are accessible in the SNZ datalab environment as part of the Integrated Data Infrastructure (IDI) since 2007, and as standalone datasets from 1997 until 2006.[16] The HLFS is a representative survey of the New Zealand resident population, and includes about 20,000 households and 30,000 working age (16 and over) people quarterly. Since 1997, the HLFS has included an annual Income Supplement in the June-quarter to collect information on labour earnings and income from other sources. Although there have been various changes to the survey in terms of question wording, coding and routing over time, we have constructed a reasonably consistent dataset over the full period.

Our main focus is the hourly wage earned by wage and salary employees. We use the actual hourly earnings of each worker's main job and restrict our analysis to workers who responded that they were employees: i.e. we exclude the wages of self-employed workers and employers who may have reported a wage. Table 1 presents the main characteristics of the data over the period. The first column pertains to all workers in all years, while the second and third columns show the characteristics of workers in 2000 and 2023 respectively. The final two columns describe the characteristics of sub-samples of workers potentially affected by the minimum wage (defined as having wages less than the following year's minimum wage) in 2000 and 2023. The first row shows that the (wage and salary) employment rate among the population increased nearly 7 ppt (14%) from 48% to 55%, between 2000 and 2023. This increase reflects both cyclical factors (the economy was coming out of a recession in 2000, and the labour market was strong in 2023), as well as some secular factors: in particular, the strong growth in employment of older workers since the 1990s (Hyslop et al. 2019).

The characteristics in the remaining rows are conditional on being in wage and salary employment. There have been notable shifts in the demographic composition of the workforce

[16] Our analysis extends the data used by Maré and Hyslop (2021), and more details of the data construction can be found in that paper. Prior to 2016, when the IS was more formally included as part of the HLFS, it was also referred to as the New Zealand Income Survey (NZIS).

over the period. Reflecting both population ageing and the increasing labour force attachment of the older population, there has been a notable change in the age structure of the workforce over the period, with the fraction of youth workers (under 25) falling from 18% to 15.5% of workers and the fraction aged 65 and over increasing from 1.1% to 5.2% since 2000. In addition, the ethnic make-up of the workforce has changed, with the fraction of workers reporting European ethnicity falling 15 ppt from 81% to 66%, and increases in the fraction of Māori, Pacifica and particularly other ethnicities.[17] There has also been an increase in the level of qualifications of workers: e.g. the fraction with no qualifications fell from 19% to 10% between 2000 and 2023, and the fraction with degree level qualifications increased from 21% to 36%.

Real wages have increased by about one-third since 2000:[18] average wages increased 33%, and average log(wage) increased 31 log-points (about 36%), implying increasing wages across the distribution with, as we will show shortly, stronger increases in the lower range of the distribution. Not surprisingly given the strong increases in the minimum wage, the fraction of workers with wages at or below the current minimum wage increased from about 2.5% in 2000 to almost 8% in 2023, and the fraction of workers *potentially* affected by the next year's minimum wage increased from 3.7% to 12% in 2023.[19] Based on the standard deviation of log(wages), wage inequality has fallen about 15% since 2000: we will see shortly that most of this is due to compression in the lower tail of the distribution.

We focus next on the samples of workers potentially affected by the minimum wage in columns 4 and 5. The patterns in these columns confirm that females, youth, non-European and less qualified workers are overrepresented among lower wage workers potentially affected by minimum wages. In particular, youth workers account for over 40% of those potentially affected, in contrast to accounting for less than 20% of the workforce. Consistent with this, workers in the three main teen-employing industries (Agriculture, Retail and Hospitality) account for 18% of employment in 2023, but 42% of those potentially affected by the minimum wage. Reflecting the strong increases in the minimum wage over the period, minimum wage affected workers have experienced much stronger real wage growth than other workers:

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[17] These fractions are based on total ethnicity reports, so can sum to greater than 1, if workers identify with multiple ethnicities.
[18] To reduce the influence of extreme wage outliers, we have left and right censored the CPI-adjusted real wage at $2.50 and $250 (2023 $-values) per hour: this affects about 0.5% and 0.9% of low and high wage observations, respectively.
[19] The fraction less than or equal to the current minimum wage reached 10% in 2008, and has been relatively stable (between 8% and 10%) since then. In contrast, the fraction less than next year's minimum reached 14% in 2007, then fell to about 9% in 2010, before gradually rising to a peak of 17% in 2021. The 2023 fraction is lower partly because of the relatively small increase in the minimum wage in 2024, which saw a reduction in its real value.

average wages among the potentially affected subgroup more than doubled,[20] compared to an increase of about one-third for all workers between 2000 and 2023.

3.2 Descriptive trends

We now elaborate on some of the period changes described in Table 1, by documenting the annual trends of various salient measures. We begin, in Figure 2, by describing the trends in the CPI-inflation adjusted minimum wage and real wages over the period. Panel (a) describes the trends in the median log(wage) for all workers, separately for youth (16-24 year olds) and adult (25-64 year olds), and the log(adult minimum wage). The median wage for all workers increases (almost universally) throughout the period, with stronger growth over 2004-09 and 2014-20; as adults dominate the workforce, adult median wages trend roughly in parallel to that of all workers. Although the overall (0.32 log-point) rise in the median wage of youth workers is similar to that of all workers, the trend increase is noticeably stronger after 2012, when the increasing minimum wage appears to be pressing on the median wage of youth.

Panel (b) of Figure 2 describes the trends in the median Kaitz indexes for all workers, youth workers and adult workers. For this exercise, we calculate a worker-specific Kaitz index based on the applicable minimum wage they faced at the time and their wage (i.e. $Kaitz_{it} = ApplicableMW_{it}/wage_{it}$), and then estimate the year-specific median Kaitz for each group. For adults and all workers, there were steady increases in the Kaitz indexes over 2000-08 and 2017-21 reflecting the stronger minimum wage increases during these periods, and roughly constant levels over 2008-17 and since 2021. For youth workers, the Kaitz index increased more strongly (50%) between 2000 and 2008 due to the youth minimum wage reforms but, as the minimum wage pressed more strongly on youth median wages, there have been smaller increases in the Kaitz index since then.

To provide more detail on the relationship between minimum wage and wage increases across the distribution, Figure 3 documents trends in various wage percentiles for all, youth and adult, and male and female workers over the period. In panel (a), we plot the trends in upper percentiles (median, 75th and 90th as dashed lines), lower percentiles (5th, 10th, and 25th as solid lines), and the minimum wage (dot-dash line) for all workers. The upper percentile trends appear broadly parallel; in fact, the total increases over the period are almost the same (32 log-

[20] Average wages increased 110%, while average log(wages) increased nearly 80 log-points (120%).

points) for each of these percentiles.[21] In contrast, the lower percentiles are more clearly affected by the minimum wage increases, particularly the 5th and 10th percentiles, which converge and are essentially the same from 2008 onwards; and the 25th percentile appears more minimum wage constrained after 2008.

We repeat the percentile trends separately for youth and adult workers in panels (b) (lower percentiles of each group) and (c) (upper percentiles). In panel (b), since 2008, the minimum wage has clearly constrained all the lower percentiles of youth wages, as well as the 5th percentile of adult wages, and appears to be affecting the 10th percentile of adult wages.[22] In panel (c), there is little evidence that the minimum wage affects the top half of the wage distributions, except possibly some effect around the median wage of youth workers. Curiously, the 75th and 90th percentiles of wages have increased relatively less for youth than adults: e.g. the 90th percentile of youth wages was 5-10% above the adult median early in the period, and has been at or below the adult median since 2008.

Panels (d) (lower percentiles) and (e) (upper percentiles) document the comparative trends for male and female workers. While female wages are lower than male wages at each quantile, there has been gradual convergence over the period. At the lower end of the distribution, since 2008 the minimum wage has reached the 10th percentile of female wages, and almost the 10th percentile of male wages. The gender wage convergence, of 3–6% across quantiles, mainly occurred during the recession following the GFC, and gain since 2016. In our analysis below, we will the relative changes in male and female wage inequality.

Figure 4 describes the trends in alternative measures of the bite of the minimum wage. For this we use the fraction of workers with wages equal to or below the current minimum wage as a measure of the fraction of workers directly affected by the minimum wage; and second, the fraction with a wage less than the next year's minimum as a measure of the fraction of workers potentially affected by the next increase.[23] There were strong increases in the bite of the minimum wage up to 2008 (particularly after 2005): the fraction of all workers with wages

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[21] Closer inspection indicates the timing of the increases vary somewhat across the percentiles – see Table 2, which also summarises trends in the 95th percentile.

[22] That the adult minimum wage is higher than the 5th and 10th percentiles of youth wages prior to 2008 is consistent with the application of the youth minimum wage. That it remains above the 5th percentile after 2008 suggests some use of the new entrants, starting out and training wages since then. In addition to these factors, non-compliance and measurement errors may contribute to the incidence of low reported wages.

[23] To the extent there are exemptions or non-compliance, these measures will overstate the true bite of the minimum wage. Also, any wage increases unrelated to the minimum wage will cause the second measure to overstate the true fraction of workers that will be affected by an increase. In analysing the 2008 policy changes that eliminated the youth minimum, while introducing a New Entrants Minimum Wage (NEMW) below the adult rate, Hyslop and Stillman (2021) found no evidence that the NEMW was used to any noticeable extent. Our interpretation is that most of the observed sub-minimum wages are the result of measurement error, and we treat them as affected by the minimum.

below or equal to the minimum more than doubled from 4.8% in 2005 to 10.2% in 2008 (panel (a)); for youth the increase started earlier, with the fraction increasing from about 3% in 2000 to 28% in 2008 (panel (b)). After 2008, the fraction of workers currently affected has remained roughly constant, ranging from 8-10% for all workers (22-30% for youth, and 4-6% for adults). The fraction of workers potentially affected by the next minimum wage increased sharply, particularly during the 2004-08 and 2017-21 periods of strong minimum wage increases: 14-17% of all workers (35-50% of youth, and 8-11% of adults) were potentially affected by increases between 2018 and 2023. However, the fact that the fraction of wages below the current minimum wage has not increased since 2008 suggests that there may be spillover effects associated with strong minimum wage increases over the latter part of the period.[24]

Finally, in Figure 5 we present trends in four standard measures of wage inequality: the standard deviation of log(wages), and the 90-10, 90-50 and 50-10 percentile differences. For all workers (panel (a)), dominated by adults (panel (c)), the 90-50 difference increased gradually up to 2015, while the 50-10 difference was mostly stable; after 2015, the 90-50 difference declined to its starting level (about 0.6) by 2023, while the 50-10 difference declined steadily (for adults from 0.48 to 0.35). As a result, the 90-10 difference first increased with the 90-50 difference increase, and then declined more sharply as both the 90-50 and 50-10 differences fell. The standard deviation for adult workers was remarkably stable (about 0.47) until 2015, before declining steadily to 0.39 in 2023.

In contrast, there were almost continuous declines in each of the inequality measures for youth wages. Loosely mirroring the adult patterns, the 90-50 difference rose over the early part of the period before declining slightly after 2004 and more steadily after 2015. The 50-10 difference declined from 0.45 in 1997 to 0.31 in 2007, followed by a sharp drop to 0.12 in 2008, and a more gradual decline to about 0.09 by the end of the period. This resulted in a more than 50% reduction in the 90-10 difference from 0.87 to 0.40 over the period (with a sharp 0.22 drop in 2008). The standard deviation of log(wages) also declined fairly steadily (30%) throughout the period, from 0.37 in 1997 to 0.21 in 2023.

We summarise the various trends shown in these figures in Table 2, which documents changes over four subperiods – 1997-2001, 2001-08, 2008-17 and 2017-23 – as well over the full

[24] Dis-employment effects associated with the minimum wage may contribute to these patterns. For example, Hyslop and Stillman (2021) concluded the 2008 youth minimum wage change resulted in employment loss for 16-17 year olds (relative to older youth employment), and the minimum was considerably more binding on youth in general by then: appendix Figure A1 shows the youth employment rate fell about 10ppt between 2007 and 2013, and didn't fully recover until 2022.

period.[25] First, the Kaitz index increased for all workers during the two subperiods of increasing minimum wages, while the increase for youth workers was largely concentrated in the period to 2008.[26] Similarly, increases in the two bite ('fraction') measures of the minimum wage were also concentrated in the period to 2008.

Second, although there is some variation in the trends, wage increases across the top half of the distribution were very similar over the full period (0.32 log points at the median, 75th and 90th, and 0.30 at the 95th percentile), and were almost identical for adult workers (0.301-0.305). In contrast, wages increased more strongly across the lower half of the wage distribution: 0.35, 0.45 and 0.61 at the 25th, 10th and 5th percentiles respectively. This lower-tail compression also occurred for adult workers, with wages increases of 0.49, 0.40 and 0.36 at the 5th, 10th and 25th percentiles respectively, compared to 0.30 at the median and higher percentiles.

Third, wage increases for youth workers were systematically weaker at higher percentiles, and stronger across the lower tail. In fact, youth wage increases monotonically declined across the distribution (ranging from 0.80 at the 5th percentile to 0.32 at the median and 0.15 at the 95th percentile), implying there has been substantial compression of youth wages over the period.

Finally, wage inequality for all and adult workers fell, largely as a result of compression in the lower half of the distribution. For youth wages, substantially stronger compression in the lower half of the distribution, combined with compression also in the top half of the distribution, resulted in even stronger reduction in inequality over the period.

4 Analysis and results

We now turn to our analysis of the effects of minimum increases on the wage distribution in New Zealand over the period.

4.1 Conceptual approach to modelling minimum wage effects

Our approach to analysing the possible minimum wage effects on the wage distribution and inequality follows that depicted in Figure 1, discussed in section 2. In particular, we abstract from any employment loss caused by minimum wage increases and focus on the observed

[25] These subperiods will be the focus of our subsequent analysis and correspond to the periods of relative minimum wage increases, except that we include 2001 in the initial period: although this was the year of the initial youth reform, the (adult) minimum wage did not increase substantially until after 2002.

[26] Arguably, this is largely because the minimum wage substantially determined youth wages (especially for teens) by 2008, thus resulting in a fairly constant Kaitz ratio after that.

distribution of wages.[27] We consider three types of minimum wage effects on wages: displacement effects on directly affected workers that will reduce the wage density below the minimum; an expected mass-point spike in the distribution at the minimum wage associated with the wages displaced from below; and possible spillover effects on wages above the minimum wage associated with maintaining wage relativities across the range around the minimum wage.

An important consideration is how to construct a suitable counterfactual distribution for changes in the minimum wage: e.g. focusing on a period with a low minimum wage, what would the counterfactual distribution be in the presence of a high minimum wage? As New Zealand has a single national minimum wage, the options for constructing counterfactual distributions are limited.[28] In our main analysis, we adapt the DFL approach of 'tail-pasting' the lower tail (below the minimum wage) of the wage distribution when the minimum is high on to the corresponding tail of the distribution when the minimum wage is low, discussed shortly.[29]

4.2 Empirical approach and results

Our approach to modelling the effects of minimum wages and other factors on the wage distribution follows that of DFL. This involves, first, applying kernel density methods to estimate the wage distributions at the start and end of the period; and second, estimating counterfactual distributions to identify the effects of the increase in the minimum wage and changes in other factors on the change in the wage distribution over the period. We focus on three sets of factors: changes in the observable sociodemographic and location characteristics of workers over the period; changes in the economic returns to those characteristics; and changes in the level of the adult minimum wage. The approach involves the sequential construction of counterfactual distributions to identify the effects of each set of factors.

[27] Assuming any employment loss is confined to workers with wages below the minimum wage, this will tend to bias upwards the estimated median wage (relative to the true latent distribution), and raise the apparent density of wages below the minimum and lower the density at and above the minimum wage. However, we expect such effects to be relatively minor: e.g. if the minimum wage is binding on 10% of workers (approximately the current fraction), and the employment response elasticity is -0.15 (about the consensus in the literature), a 20% increase in the minimum wage would result in about 0.3% employment loss.

[28] US research commonly exploits state variation in minimum wages over time. More recently, US (Wiltshire, McPherson, and Reich 2023) and UK (Giupponi et al. 2024) research has used regional variation in relative wages that affect the bite of common minimum wages. Although wages do vary regionally in New Zealand, the variation appears to be relatively small.

[29] In secondary analysis of spillover effects, discussed in Appendix 1, we assume that, in the absence of minimum wage changes, the overall wage distribution is stable around the median. This implies there would have been balanced annual wage growth across the distribution, equal to the growth in the median wage. Given the comparatively stable trends for wages in the top half of the distribution, together with the stronger growth in the lower percentiles being consistent with minimum wage effects documented in the previous section, we believe this is a reasonable assumption. We then use distribution-regressions (Foresi and Peracchi 1995; Fortin, Lemieux, and Lloyd 2021) to estimate the underlying wage distribution and model minimum wage effects below-, at- and above- the minimum relative to year-specific median wages.

We begin by introducing some notation. First, each individual observation consists of the vector (w, x, t), where w is log(wage), x a vector of observable covariates with domain Ω_x, and t a time period. We are interested in analysing the change in wages over the sample period, and use "*t=0*" and "*t=1*" to denote the four years at the start (1997-2000) and end (2020-2023) of the period respectively. The actual distribution of wages in period-t can be represented by the unconditional density, $f_t(w)$:

$$f_t(w) = \int_{x \in \Omega_x} f(w|x, t_w = t, m_t) dF(x|t_x = t)$$
$$= f(w;\ t_w = t, t_x = t, m_t)$$

where m_t is the period-t minimum wage, and the "w" and "x" subscripts on the t variables represent the 'structure' of wages (represented by the conditional density of wages) and the distribution of covariates are in period- t, as subsequent counterfactual wage densities will be constructed based on different timings of these variables. That is, the unconditional density at wage-w (($f_t(w)$)) can be obtained by integrating the conditional density over the domain of the covariates. This can be estimated from the sample data using kernel density methods:

$$\hat{f}_t(w) = \sum_{i=1}^{N_t} \frac{\theta_{it}}{h} K\left(\frac{w - w_{it}}{h}\right)$$

where w_{it} and θ_{it} are worker-*i*'s log(wage) and sample weight in period- t ($\sum_{i=1}^{N_t} \theta_{it} = 1$) respectively, $K(.)$ is the kernel function and h is the bandwidth. We use the HLFS sampling weights, an Epanechnikov kernel function, and a bandwidth of 0.01 throughout the analysis.[30]

We first describe the estimated kernel densities for the t=0 and t=1 periods in Figure 6. In panel (a) we graph these two distributions, together with a simple counterfactual distribution in which the t=0 wages have been adjusted by the median real wage increase between the periods.[31] In panel (b) we graph the density changes between the actual distributions over the period, and the changes implied by the simple median-adjusted counterfactual; and in panel (c) we graph the actual density changes together with the difference between the actual and

[30] Our estimation uses Stata's kdensity function. The 0.01 bandwidth is smaller than the 'optimal' bandwidth (chosen to minimise the mean integrated squared error based on an assumption of Gaussian-distributed wage data and a Gaussian kernel) – e.g. the optimal bandwidth using all years is about 0.029. A narrower bandwidth results in a noisier estimate of the kernel density function but better reveals localised shifts in a distribution.

[31] That the upper tail wage quantile increases documented above have been remarkably similar, together with the assumption that the minimum wage changes do not affect the median wage, we believe that median-adjusted wage distribution provides a plausible counterfactual for changes in the absence of the minimum wage increases over the period.

median-adjusted changes.[32] Each figure includes three vertical lines, corresponding to the (highest) minimum wages in each the t=0 and t=1 periods and the median wage in t=1.

Three features are apparent from panel (a). First, the minimum wage appears to be largely non-binding in the early period.[33] Second, by the later period, the minimum wage had a substantial effect on the lower tail of the distribution, resulting in a clear drop in the density below, and a large spike at, the minimum wage. Third, consistent with the strong trend increases in wages at all percentiles of the wage distribution shown in Figure 3, the median-adjusted wage distribution shows there was a substantial rightwards shift in wages over the period; and the similarity of the top half of this counterfactual and the actual t=1 distribution confirms there balanced wage growth above the median.

The actual density changes shown in panels (b) and (c) show a large decline in density at wages below the latter period minimum wage, and increase in density at wages above that level, with a sharp shift from density loss to gain around that later minimum wage point. The changes implied by the median-adjusted counterfactual distribution in panel (b) account for sizeable proportions of the reduction in density below the minimum wage, and the increase between the minimum and median wages, and most of the increase above the median wage. The non-median-adjusted (residual) changes shown in panel (c) provides an alternative view: as the raw median-adjustment to wages does not affect wage relativities, it is these changes which drive changes in wage inequality measures of interest. For this reason, in our subsequent analysis, we will first condition on the raw median-adjusted wage changes presented here.

Using these pooled samples, we estimate various wage inequality measures, reported in the first two rows of Table 3. We include the 90-10, 90-50 and 50-10 log(wage) differences, the standard deviation of log(wages), and the Gini coefficient associated with the wage level. These show broad reductions in wage inequality associated with the lower half of the wage distribution, in line with the annual trends shown in Figure 5. For example, the 90-10 difference declined 10% from 1.06 to 0.95 between 1997-2000 and 2020-2023: this combined a small (4% or 2.4ppt) increase in 90-50 difference, and a larger (28% or 13.2ppt) decline in the 50-10 difference. The standard deviation and the Gini coefficient declined 16% and 11% respectively.

[32] As discussed above (footnote 18), we have left- and right-censored wages at $2.50 and $250 (2023-$) for our analysis. But, to better manage the visual effects on the wage distribution, we have left and right-censored real log(wages) at 2.25 and 4.75 (approximately $9.50 and $115 per hour) for the density estimation.

[33] The noticeable spike in the PDF around $18 is associated with large numbers of workers earning $10-$12 nominal wages in the early period. For example, deflated by the change in the average CPI in the start and end periods, the spike at $18.20 (real) corresponds to a nominal wage of about $11.

Our primary objective is to analyse the contributions to the decline in wage inequality associated with changes in individual characteristics, economic returns, and the statutory minimum wage over the period. We do this by constructing counterfactual distributions for each of these factors in turn, and then use these counterfactuals to estimate the resulting contributions to the change in wage inequality. As the results may depend on the sequential ordering of the factors, we also estimate the effects associated by sequencing the minimum wage increases first, followed by the changes in characteristics and economic returns.

4.2.1 Changes in observable characteristics

We start by considering the effect of changes in the characteristics of workers over the period. As seen in Table 1, there were several significant demographic shifts among workers over the period. These include workforce ageing, both due to population ageing in general and also the increase in the employment rate of older workers (e.g. the youth share of the workforce fell from 18% to 15.5%); increasing levels of formal qualifications (the share of workers with no qualifications fell from 19% to 10%, and the share with degree qualifications increased from 21% to 36%); and substantial changes in the ethnic make-up of the workforce – e.g. the European share of workers fell from 81% to 66% and the share of other (non-European, non-Māori and non-Pacifica) workers increased from 5% to 21%. To the extent that the wages associated with such characteristics vary, there may have been a noticeable effect of the distribution of wages associated with these changes.

To estimate the effect of changes in worker characteristics over the period, we construct a counterfactual distribution for wages assuming the wage structure and minimum wage remain as in t=0, but the distribution of worker characteristics is as in t=1. Assuming the structure of wages does not depend on the distribution of characteristics, the counterfactual density can be expressed as

$$f_x(w;\ t_w = 0, t_x = 1, m_0) = \int_{x \in \Omega_x} f(w|x, t_w = 0, m_0) dF(x|t_x = 1)$$

$$= \int_{x \in \Omega_x} f(w|x, t_w = 0, m_0). \psi_x(x). dF(x|t_x = 0)$$

where $\psi_x(x) = dF(x|t_x = 1)/dF(x|t_x = 0)$ is a reweighting function that acts to up-weight t=0 observations that have characteristics more prevalent in t=1, and down-weight observations with characteristics less prevalent in t=1. Bayes' rule can be used to re-express $dF(x|t_x = t)$ in the numerator and denominator, and $\psi_x(x)$ rewritten as:

$$\psi_x(x) = \frac{P(t_x = 1|x)/P(t_x=1)}{P(t_x = 0|x)/P(t_x=0)}.$$

This expression involves the ratio of the conditional probability of being observed in t=1 versus t=0, which can be estimated using a standard binary response model, normalised by the ratio of the unconditional probabilities (i.e. weighted sample shares).

We operationalise this reweighting function by estimating a logit model for $P(t_x = 1|x)$ for the pooled sample of t=0 and t=1 observations. The vector (x) of characteristics includes a quartic polynomial in age, and indicator controls for gender (female), mutually exclusive ethnicity groups (European only, Māori only, European and Māori, Pacifica only, and other ethnic responses), highest qualification (no qualifications, school, post-school, and university level qualifications), and region (17 local government regions). Combining the predictions from this estimation ($\hat{P}(t_x = t|x)$) with the unconditional (weighted) observation shares for each period (i.e. $\hat{P}(t_x = t)$), provides predicted reweighting function, $\hat{\psi}_x(x_i)$. The counterfactual (median-adjusted) wage distribution can then be estimated using kernel density estimation applied to the reweighted t=0 sample:

$$\hat{f}_x(w) = \sum_{i=1}^{N_0} \frac{\hat{\psi}_x(x_{i0})\theta_{i0}}{h} K\left(\frac{w - w_{i0}}{h}\right).$$

We graph this counterfactual distribution in the left hand side of Figure 7(a), together with the median-adjusted 1997-2000 wage distribution (and, faintly, the 2020-2023 distribution); and show the contribution to the change in density over the period $\left(\hat{f}_x(w) - \hat{f}_0(w)\right)$ in the right hand figure. The effects of the covariate changes appear to be comparatively small, however they are predicted to reduce the density of lower wages (roughly below the median wage) and increase the density of higher wages, consistent with a hypothesis of human capital upgrading over the period.

The estimated contributions of changing characteristics to changes in wage inequality over the period are shown in the fourth row of Table 3. Although the visual effects of the changing characteristics on the wage distribution appear minor, they are estimated to <u>increase</u> wage inequality. In fact, they are predicted to contribute more than all (128%) of the small (4%) increase in the observed 90-50 difference, and contribute between -12% (50-10 difference) and -56% (Gini coefficient) to the <u>decreasing</u> inequality in the other measures.

4.2.2 *Changes in returns to observable characteristics*

The second factor we examine is the changes in the economic returns to characteristics over the period. Given the raw-median adjustment accounted for previously, we focus on the relative changes in returns to worker characteristics. Because of possible minimum wage effects on average wages, we choose instead to provide a quantile-based adjustment for economic returns. To do this, we assume that any effects of the minimum wage do not affect wages in the top half of the distribution, and apply estimates of the unconditional (marginal) median wage change conditional on covariates over the period. This involves applying the recentred influence function (RIF) approach of Firpo et al. (2009; 2018) to estimate the unconditional median wage function separately in t=0 and t=1.[34] We then adjust the observed wages in t=0 for the predicted median increase in the wage for each worker.

In particular, we estimate a returns-adjusted log(wage) for each t=0 worker: $\widehat{w}_{i0} = w_{i0} + x_{i0}{}'(\hat{\beta}_1 - \hat{\beta}_0)$,[35] where $\hat{\beta}_t$ is the estimated coefficient vector from the RIF median regression conditional on x_i. The resulting counterfactual distribution for wages given the estimated changes in characteristics and median wages, is expressed as:

$$f_{xr}(\widehat{w};\ t_w = 0, t_x = 1, m_0) = \int_{x\in\Omega_x} f(\widehat{w}|x, t_w = 0, m_0) dF(x|t_x = 1)$$

$$= \int_{x\in\Omega_x} f(\widehat{w}|x, t_w = 0, m_0). \psi_x(x). dF(x|t_x = 0).$$

This can be estimated applying kernel estimation to the t=0 sample-adjusted log(wage) and reweighted for the characteristics:

$$\hat{f}_{xr}(w) = \sum_{i=1}^{N_0} \frac{\hat{\psi}_x(x_{i0})\theta_{i0}}{h} K\left(\frac{w - \widehat{w}_{i0}}{h}\right).$$

This estimated wage distribution is shown in the left hand side of panel (b) in Figure 7, together with the previous characteristics-adjusted counterfactual (from panel (a)) and the actual 2020-2023 wage distribution; and the right hand figure shows the predicted (marginal) contribution to the overall density changes $\left(\hat{f}_{xr}(w) - \hat{f}_x(w)\right)$. The estimated relative returns

[34] As the 'economic returns' adjustment follows the change in attributes, we estimate the t=0 RIF using the estimated reweights ($\hat{\psi}_x(x_i)\theta_i$), and the t=1 RIF using the original weights (θ_i). Because the unconditional quantile estimates can be expressed as a weighted average of conditional quantile estimates (at the unconditional quantile), this approach is still susceptible to possible minimum wage effects; however, we believe such effects will be less than on average wages. As robustness checks, we also estimate conditional median and average (mean) wage adjustments.

[35] For t=1 observations, $\widehat{w}_{i1} = w_{i1}$. For the minimum wage adjustment below, we will use the $\widehat{w}_i$ notation, but with the understanding that $\widehat{w}_{i1} = w_{i1}$.

adjustment tends to smear mass away from local wage spikes in the distribution, resulting in a relatively lumpy redistribution effect.

The estimated contributions of the economic returns to wage inequality changes over the period are shown in the fifth row of Table 3. The contributions are all mildly negative, meaning the changes in returns acted to reduce inequality, and account for between 7% and 13% for the declining measures, and -9% for the increasing 90-50 difference. As a constant wage adjustment for all workers that didn't affect relative wages would have no effect on wage inequality, this implies the estimated returns were modestly higher for worker characteristics associated with comparatively low wages.

4.2.3 Changes in the minimum wage

The final factor we consider is that of changes in the statutory minimum wage over the period. For this, we follow DFL's approach of replacing the tail of the t=0 (1997-2000) wage distribution below the minimum wage that prevails in t=1 (m_1), with the equivalent tail of the t=1 distribution. For this to provide a valid counterfactual for the impact of the increase in the minimum wage requires three conditions are met: first, the minimum wage has no employment effects, so there is no density loss below the minimum wage in t=1; second, the shape of the conditional density of wages at or below the minimum wage depends only on the level of the minimum wage; and third, the minimum wage has only "direct" effects on wages below the minimum wage, and no spillover effects above the minimum. We will return to the issue of spillovers subsequently.

The second condition implies that the conditional density below m_1 that would have prevailed in t=0 if the minimum wage was m_1 is proportional to the conditional density below m_1 in t=1. In practice, sequencing the effect of the minimum wage following that of changes in worker attributes and economic returns, we replace the tail of that counterfactual distribution below m_1 with the corresponding tail from the t=1 distribution, reweighted to ensure the resulting distribution integrates to 1. That is, the counterfactual density can be expressed as:

$$f_{xrm}(\widehat{w};\ t_w = 0, t_x = 1, m_1) = \int_{x\in\Omega_x} f(\widehat{w}|x, t_w = 0, m_0) dF(x|t_x = 1)$$

$$= \int_{x\in\Omega_x} \big\{1(\widehat{w} \le m_1) f(\widehat{w}|x, t_w = 1, m_1). \psi_w(x, m_1). dF(x|t_x = 1) + \big(1 - 1(\widehat{w} \le m_1)\big) f(\widehat{w}|x, t_w = 0, m_0). \psi_x(x). dF(x|t_x = 0)\big\}.$$

where $1(\widehat{w} \le m_1)$ is an indicator function for whether the log(wage) $\widehat{w}$ is below m_1, and $\psi_w(x, m_1) = P(\widehat{w} \le m_1|x, t_w = 0)/P(\widehat{w} \le m_1|x, t_w = 1)$ is a reweighting function to ensure the lower tail densities match and the overall distribution integrates to 1. Again, applying Bayes rule to the numerator and denominator in $\psi_w(x, m_1)$, gives

$$\psi_w(x, m_1) = \frac{P(t_w = 0|x, \hat{w} \leq m_1)/P(t_x=0|x)}{P(t_w = 1|x, \hat{w} \leq m_1)/P(t_x=1|x)}.$$

We estimate a logit model for $P(t_w = 1|x, \hat{w} \leq m_1)$, and can then estimate $\hat{\psi}_w(x, m_1)$ based on the resulting predictions.[36]

We again use kernel density methods to estimate the counterfactual for changes in worker characteristics, economic returns and the minimum wage:

$$\hat{f}_{xrm}(w) = \sum_{i=1}^{N_1} 1(\hat{w}_{i1} \leq m_1) \frac{\hat{\psi}_w(x_{i1}, m_1)\theta_{ii}}{h} K\left(\frac{w - \hat{w}_{i1}}{h}\right)$$
$$+ \sum_{i=1}^{N_0} \left(1 - 1(\hat{w}_{i0} \leq m_1)\right) \frac{\hat{\psi}_x(x_{i0})\theta_{i0}}{h} K\left(\frac{w - \hat{w}_{i0}}{h}\right).$$

This estimated wage distribution is shown in the left hand side of Figure 7(c), together with the previous characteristics and returns adjusted counterfactual (from panel (b)) and the actual 2020-2023 wage distribution; and the right hand figure shows the predicted (marginal) contribution to the overall density changes $\left(\hat{f}_{xrm}(w) - \hat{f}_{xr}(w)\right)$. These show the predicted minimum wage effect reduces the density below the minimum wage, consistent with minimum wage compliance, and this density is shifted to a mass point at m_1. By construction, the minimum wage counterfactual has no effect on the distribution above the minimum wage. Comparing the distributions on the left-hand side, this counterfactual appears to fit the tail of the 2020-2023 distribution below the minimum wage reasonably well, although the spike at m_1 is larger than in the actual distribution, and consequently the actual density between m_1 and the median wage is underestimated.

The estimated contributions of the minimum wage to wage inequality changes over the period are shown in the sixth row of Table 3. These imply the minimum wage increases contributed substantially to the reduced inequality across the measures (except the 90-50 which was unaffected). Of most proximate relevance, it accounts for the vast majority (89%) of the reduction in the 50-10 difference measure, and 58% of the reductions in the Gini and 109% of 90-10 difference reduction.

We summarise the combined contributions of the three sets of factors graphically in Figure 7(d). The left-hand panel compares the counterfactual wage distribution (i.e. the "+Min

[36] Note that, the resulting reweighted density in the lower tail from the t=1 distribution does not quite equal the lower tail density the t=0 distribution because of non-linearities. To ensure the densities match we make a subsequent adjustment.

wage" distribution in panel (c)), with the actual 1997-2000 and 2020-2023 distributions; while the right-hand panel compares the combined (explained) changes and the actual changes. These factors explain the changes in the lower part of the distribution and the top half of the distribution well, but overpredict the decline in density over the (roughly) 10% range just below m_1, and underpredict the increase in density between m_1 and the current median. The combined 'explained' contribution to changes in inequality are documented in Table 3. These show that most (75–119%) of the changes in the upper- and lower tail quantile differences are explained by the three sets of factors considered, about half of the change in the standard deviation, and little (13%) of the change in the Gini coefficient.

4.2.4 Robustness to sequencing

As this analysis involves the sequential construction of counterfactuals, the decomposition results may depend on the particular sequencing adopted. To assess the robustness of the results, we next consider sequencing the minimum wage changes before the changes in worker characteristics and economic returns. Given the strong wage growth over the period, adjusting the initial period wages is particularly important in this case as it dramatically affects the size of initial period lower tail (below the later period minimum wage).

The construction of the counterfactual densities follows by analogy to those described earlier, but requires some necessary adjustments which have some material effects on the resulting changes. In particular, as the minimum wage adjustment involves replacing the lower tail of the wage distribution in the initial period with that from the later period, the later period's distribution of characteristics needs to be adjusted to match that of the initial period, and also latter period wages need to be rescaled for the change in returns. To make these adjustments, we first adjust t=1 sampling weights by $\psi_x^{-1}(x)$, and wages: $\widehat{w}_{i1} = w_{i1} - x_{i1}'(\hat{\beta}_1 - \hat{\beta}_0)$. The former acts to reweight the reweighting function $\psi_w(x, m_1)$ applied to the t=1 tail by multiplying by $\psi_x^{-1}(x)$, while the latter rescaling acts to define the tail as where $\widehat{w}_{i1} \leq m_1$. The subsequent covariate and returns adjustments proceed as previously by conditioning on this (counterfactual) tail-pasted sample and wages as the 'initial' (t=0) sample, together with the final (t=1) actual sample.

We present the sequential counterfactual distributions, together with their implied marginal changes, based on this sequencing in Figure 8. Although the effects of the factors are broadly similar to the original ordering discussed above, the necessary reweighting and rescaling adjustments for the minimum wage effects result in some (potentially unattractive) differences.

First, because of variation in the characteristics of workers paid the minimum wage (or other salient wages), the returns rescaling acts to disperse density away from these points. To the extent the minimum wage effects dominates this variation, the resulting mass at the minimum wage will understate the true spike. Second, the covariate adjustment effects, described in panel (b) of Figure 8, suggest a noticeably larger rightwards shift in the wage distribution than we found in the prior ordering, and a particularly large decrease in the density below m_1. This appears to be due to the tail-pasting resulting in a substantial change in the distribution of covariates in the counterfactual (t=0) distribution.[37] The estimated drop in density below m_1 associated with the change in covariates is partly counterbalanced by an increase associated with the returns.

We summarise the marginal contributions to the change in wage inequality measures in the second panel of Table 3. The alternative ordering contributions of the various factors to inequality changes differ somewhat from those of the main sequence discussed earlier, reflecting the visual differences in the corresponding counterfactual distributions in Figure 7 and Figure 8. In particular, the minimum wage adjustment account for less of the change in each inequality measure – e.g. 54% (compared to 89% above) of the change in the 50-10 difference, and 66% (72%) of the change in the standard deviation of log(wages); and the fractions of the changes accounted for by all factors are lower – e.g. 30% (83%) of the change in the 50-10 difference, and 40% (48%) of the change in the standard deviation.

We have considered an alternative approach to this ordering that addresses the reweighting and rescaling issues discussed above with regards to this sequencing. First, rather than replacing the t=0 lower tail sample with the pasting the t=1 sample, we instead maintain the t=0 sample of workers and simply replace their wages in the lower tail with the equivalent ranked wages from t=1 tail. Second, we do not rescale the wages for the estimated change in relative returns.[38] One argument against the rescaling is that if minimum wages are one source of the change in relative returns, then this will be captured by the rank-replacement by the (t=1) actual wages. That is, this ordering gives precedence to any minimum wage effects with the regression-adjusted returns secondary, while the main ordering above does the opposite.

[37] That is, lower tail ($\leq m_1$) wage workers in the t=0 and t=1 distributions consist of the same (t=1) subsample (albeit with different sampling weights). Because there was a broader range of (skill) attributes among lower-wage workers when the minimum wage was (largely) non-binding in t=0 than in t=1, the tail-pasting results in a greater concentration of lower skilled attributes in the counterfactual (t=0) distribution, and the subsequent covariate adjustment results in larger upskilling.

[38] Rescaling could easily be done before the relative-rank replacement described here. However, this has the effect of smearing the mass at the spike.

We present the counterfactual distributions based on this approach in appendix Figure A2. As expected, it results in a much sharper spike in wage distribution at the minimum wage (panel (a)), while the covariate adjustment (panel (b)) is more in line with that observed for the main ordering. However, the returns-adjustment (panel (c)) shows similar smearing effects around the minimum wage and other localised spikes in the wage distribution. As a result, the visual patterns from this approach tend to lie somewhere between those displayed in Figure 7 and Figure 8. The estimated contributions to inequality are shown in the lower panel of Table 3, and reflect these patterns. The relative contributions of the minimum wage, covariate and returns contributions are broadly similar to those estimated for the main order: e.g., the estimated minimum wage contributions to the fall in the 50-10 difference and standard deviation here are 82% and 72% respectively.

Given the reweighting and rescaling issues associated with modelling the minimum wage effects first, we prefer the original sequence of analysis. Nonetheless, the various approaches provide broadly consistent results, showing large equalising effects of the minimum wage increases on wage inequality (particularly on the lower tail), modest increases in inequality associated with changes in worker characteristics, and modest decreases associated with changes in the relative returns to those characteristics. Overall, the top half of the distribution has been remarkably stable (allowing for median wage growth), while the three sets of factors considered tend to underestimate the fall in density below the minimum wage, and underestimate the increase in density between the minimum and median wages.

4.3 Additional analysis

We now consider various extensions and robustness checks to the analysis discussed in the previous subsection. These include subperiod analyses; possible gender differences in wage inequality changes; and possible spillover effects associated with the minimum wage increases.

4.3.1 Subperiod analyses

First, we analyse the effects of changes in the three sets of factors over the two subperiods, from 1997-2000 to 2009-12 and from 2009-12 to 2020-23. The first subperiod covers the period of minimum wage increases and youth minimum wage reforms in the 2000s, while the second subperiod covers the recent period of minimum wage increases. We summarise the results for these subperiods visually in Figure 9, and the inequality statistics in Table 4. In Figure 9, the left-hand panels summarise the first sub-period and the right-hand panels the second sub-period: the top panels ((a) and (d)) show the actual wage distributions at the start and end of each subperiod, together with the median-wage adjusted initial distribution; the middle panels ((b) and (e)) compare the combined explained changes and actual changes (including the median-wage changes) over the subperiod; and the bottom panels ((c) and (f)) compare the residual and actual changes.

Inequality over the first subperiod wage, summarised in the first panel of Table 4, was comparatively stable, with small increases in the standard deviation (3%) and the Gini (6%) measures, a small drop in lower tail (50-10) inequality (4%), and a 12% increase in upper tail (90-50) inequality. Because of the latter change, median-adjusted counterfactual fits the top half of the 2009-12 distribution less well than over the full period. However, the changes are fairly well explained by the three sets of factors. The effects of each work similarly to those described for the full period in Figure 7. Changes in worker characteristics and returns have comparatively small effects, that each act to increase inequality; while the minimum wage increases account for the clear deficit below, and spike at, the higher minimum wage, and reduce the lower tail, standard deviation and Gini measures. This suggests there was a modest increase in inequality over this period that the minimum wage increases acted to counter in the lower tail.

In comparison, changes over the second period were more substantial. Figure 9(d) shows a clear decrease in density below the higher minimum and increase in the spike at the minimum wage, together with an increase in density between the minimum and median wage. The combined effects fit the shift in density around the lower minimum well, but overfit the increase in density at the higher minimum and underfit the higher density between this minimum and the median wage, consistent with spillover effects on wages above the minimum being important by the end of the period. The second panel in Table 4 summarises the contributions to inequality changes over this subperiod. The 25% drop in lower tail (50-10 difference) inequality was the main change, although the 90-50 difference also fell 7%, contributing to a 17% decrease in the standard deviation of log(wages) and 16% fall in the Gini coefficient. Changes in worker characteristics are again predicted to mildly increase inequality, the estimated changes in returns contributed relatively strongly (25-55%) to the fall in inequality, and minimum wage changes accounted for smaller fractions: 40% of the 50-10 change, and less of the other measures.

From these subperiod analyses, it appears that possible spillover effects associated with minimum wage increases only started to occur after 2012. Given the minimum wage increases until 2017 were largely in line with (median) wage increases, we attribute the advent of spillovers occurred during the period from 2018, consistent with preliminary analysis in Maré and Hyslop (2021). There are at least two possible reasons for this. First, as the minimum wage primarily affects youth workers and, until recently had little effect on adult wages, there may have been little spillover pressure on wages above the minimum if firms simply treated the minimum as the de facto youth wage. As seen in Figure 4, the fraction of youth workers paid at or below the minimum wage reached 10% in 2002 and has been 20-30% since 2008, while the fraction potentially affected by the next-year's minimum wage has been 30-50% since 2018. In contrast, although there was a step-increase in the fraction of adult workers with wages affected by the current minimum in 2006, the fraction has remained between 4% and 6% since, while the fraction potentially affected by the next-year's minimum increased noticeably to 8-11% in the last few years.

Second, there have been various pay equity agreements, such as the Care and Support Worker Pay Equity Settlement (Ministry of Health 2017), that may have confounding effects proximate to the minimum wage. From a descriptive analysis of potentially affected Care and Support workers, it appears that this alone provides a relatively modest (less than one-third at most) contribution to the apparent spillover effects observed recently. However, together with other settlements, such agreements may have had substantial effects on the observed range of spillovers. We address this issue in the next two sections.

4.3.2 Gender differences

Next, we analyse changes in the wage distributions and wage inequality of male and female workers separately. We do this for two reasons: first, because females have lower wages and more likely affected by minimum wages than males; and second, if there have been significant wage effects associated with the recent pay equity agreements, they should present as more noticeable effects on female wages. We summarise the results in Figure 10 and Table 5.

In Figure 10, we first describe the wage distributions over the start (1997-2000) and end (2020-2023) of the sample period, together with the median wage adjusted distributions, separately for males and females in panels (a) and (d) respectively. The distributions are broadly similar, although the female distribution has noticeably more density at lower wages and a more prominent shoulder around the minimum wage at the end of the period.

In panels (b) and (e), we show the combined 'explained' changes in the male and female wage distributions together with the actual changes over the period; while panels (c) and (f) compare the actual and 'unexplained' (residual) changes.[39] Consistent with the analysis above, these factors account reasonably well for lower-wage changes (i.e. below the current minimum wage) and for changes above the respective current median wages, but overfit the increases in mass around the current minimum wage and underfit the increase in density between the minimum and median wage. One notable difference between these gender-specific results is that the explained factors account for noticeably more of the change in the density between the minimum and median wages for females than males: they account for about 40% of the increase for females (largely due to the estimated increase in density associated with higher returns to covariates) compared to about 15% for males. This is consistent with the hypothesis that pay equity agreements have contributed to the increase in wage density in this range.

We summarise the changes in wage inequality measures, and contributions to these changes, for males and females in Table 5. Panel (a) summarises the changes described in Figure 10 over the full period; while and in panel (b) we summarise changes over the second half of the period (2009-2012 to 2020-2023), which narrows the focus around the pay equity settlements since 2017. Across the various measures, female wage inequality is about 10-15% lower than male inequality, but the relative changes for men and women are more similar. One difference across the measures in terms of changes time is that while the lower tail (50-10) difference decreased steadily across, each of the other measures increased somewhat over the first half of the period before falling over the second half.[40]

Focusing on the 50-10 wage difference, the relative change is slightly greater for females (-32%) than males (-30%). There are two noticeable differences in the contributions for men and women. First, the estimated effects of covariate changes were inequality increasing on female wages (accounting for -21% of the decrease in the 50-10 difference), while they had a small inequality decreasing effect for males (6% contribution to the estimated change). Second, the estimated minimum wage effect on the decrease in the 50-10 difference was somewhat larger for women (-0.13, 101% of the total) than for men (-0.11, 72% of the total). These differences aside, the estimated effects of changing returns (4-6% contributions), and the (unexplained) residual (16-17% of the totals) were similar for men and women. (Also, not shown in the table,

[39] For this analysis we compare the actual rather than median-wage adjusted changes because females have experienced relatively stronger wage growth than males over the period (see Figure 3) – e.g., the median female wage increased 0.30 log points (35%) between the initial and final periods analysed here, compared to 0.24 log points (27%) for males. Much of these gender differences appear to have occurred since 2016: because there is concern that they may reflect policy effects associated with the pay equity settlements, we choose to compare actual wage changes.
[40] Except for the top-tail (90-50 difference) which increased slightly (4% for women and 9% for men), the inequality measures fell by 9-32% over the full period.

most of the residual changes can be accounted for by minimum wage spillover effects up to 0.125 log-points above the minimum wage: 90% for men and 110% for women.)

The patterns of standard deviation of log(wages) changes are similar for women, except that the minimum wage contribution is relatively smaller (77%) and the residual is larger (43%). For male wages, the covariate changes had an increasing effect on the standard deviation (-26% of the estimated change), the minimum wage had a similar effect (74% contribution) and the residual is also larger (40%). Minimum wage spillover effects account for about half of the residual changes in the standard deviation measure.

Next consider the changes over the second half on the period, shown in panel (b) of Table 5. The fall in wage inequality since 2000 was largely concentrated in this period: i.e. 78% (men) and 86% (women) of the fall in the 50-10 difference occurred during this period, and each of the other measures fell after rising between 1997-2000 and 2009-2012. However, the minimum wage appears to have contributed relatively less to these subperiod changes compared to the full period changes. For example, minimum wage effects account for less than one-quarter (23%) of the fall in the 50-10 difference for men, and about half (49%) for women, and smaller shares of the fall in the standard deviation of log(wages) (20% for men, and 32% for women). In contrast, we estimate that changes in the returns to covariates acted to reduce inequality more: e.g., explaining about half of the falls in the 50-10 difference in men's and women's wages.

In summary, the gender specific results are similar to the combined analysis discussed above. There are noticeable recent increases in density between the current minimum and median wages for both males and females. About two-thirds of the increase for women since 2009-12 is accounted for by changes in returns to observed characteristics, compared to about 40% for men. We believe these gender differences provide some circumstantial evidence consistent with pay equity settlements contributing to the changes in this range. The remaining residual density changes are consistent with minimum wage spillover effects over this range.

4.3.3 Minimum wage spillovers

Finally, the unexplained increase in density over the range between the current minimum and median wages apparent in Figure 7(c), suggests that spillover effects of the minimum wage may be important. To explore this issue, we first adapt the distribution regression approach developed by Foresi and Perrachi (1995), and used by Fortin et al. (2021) (FLL) to analyse minimum wage spillovers. We summarise the method and results here and provide a more detailed discussion in Appendix 1.

The distribution regression approach entails modelling a stable counterfactual cumulative density function (CDF) for wages, together with minimum wage effects relative to the year-specific normalised minimum wage, controlling for demographic and other factors that may vary across the distribution. We use data over the full period (1997-2023), and assume that, in the absence of minimum wage effects, the wage distribution in any year is constant except for a possible aggregate median wage change. To implement the distribution regressions, we normalise real wages relative to the annual median wage: $w_{it} = \log(wage_{it}) - med_t(\log(wage_{it}))$. We then divide the normalised w_{it} distribution into 47 intervals (with 46 cutoffs, w_k),[41] and use this structure to estimate the 46 stacked distribution regressions for the binary outcomes $P(w_{it} > w_k|X_{it})$.[42] We measure the effects of the minimum wage using 0.05 log-point intervals, centred on the minimum wage and over a fairly wide range from -0.275 log-points below, to 0.325 log-points above, the minimum. As the effects may vary according to how much the minimum wage bites, we also allow the effects to vary across four subperiods that correspond roughly to periods of relatively stable versus increasing minimum wages (1997-2001, 2002-2008, 2009-2017, and 2018-2023).

The results of this exercise are summarised in the appendix Table A1. Although somewhat inconclusive overall, for the latter three subperiods there is systematic evidence of negative effects on the density just below the minimum, positive effects at the minimum wage, and some evidence of positive (spillover) effects in the two intervals above the minimum, particularly in the final subperiod (2018-2023).

Given this pattern of results, we extend the DFL counterfactual analysis above to allow the minimum wage effects to include spillovers up to 0.125 log points above m_1. We do this by repeating the tail-pasting exercise applied to the tail below $(m_1 + 0.125)$: i.e. replacing the tail of the t=0 distribution ($\widehat{w}_{i0} < m_1 + 0.125$), with the corresponding (reweighted) tail from the t=1 distribution.

The estimated wage distribution with spillovers (not shown) fits the actual 2020-2023 distribution noticeably better below and around m_1; but overpredicts the density over the

[41] The intervals are chosen based on the mass of the data but also considering our focus on minimum wage effects, and reflect the right-skewed nature of the log(wage) distribution, which has grown stronger over time partly driven by the increasing minimum wage. In particular, the intervals are the left tail ($w_{it} < -0.975$), 40x0.05 log-point intervals (centred on -0.95, …, 0, … 1.00), a 0.075 log-point interval [1.025,1.10], 4x0.1 log point intervals (centred on 1.15, …, 1.45), and the right tail ($w_{it} > 1.5$). The associated cutoffs, $w_k \in (-0.975, -0.925, \dots, -0.025, 0.025, \dots, 1.025, 1.1, \dots, 1.5)$.

[42] In contrast to Foresi and Perrachi, who estimated logit models, and FLL who estimated probit models, we estimate linear probability models. This facilitates a simple and direct translation of the estimated parameters from the model in terms of effects of the minimum wage on the CDF of wages, to the fractions of mass missing at various points below the minimum wage, the fraction of excess mass at the minimum wage and, corresponding to spillover effects, the fractions of excess mass at points above the minimum wage.

spillover range (up to $m_1 + 0.125$), partly because of the underfit between $(m_1 + 0.125)$ and the median wage associated with the spillover counterfactual having no effect in this range. The estimated marginal contributions of the minimum wage spillovers to wage inequality changes (shown in the eighth row of Table 3) suggests the estimated spillovers account for about 20% of the wage inequality changes associated with the lower tail, and much of the residual changes in row 7. In particular, it accounts for nearly all of the residual changes in the 90-10 and 50-10 differences, about 40% of the residual standard deviation of log(wages) changes and about 30% of the residual Gini change.

5 Concluding discussion

New Zealand's statutory minimum wage has increased strongly since 2000 and accompanied by noticeably stronger wage growth across the lower half distribution than the top half, resulting in significant reduction in wage inequality. This paper analyses the contribution of the minimum wage increases to this decline in wage inequality. In doing this we also consider the effects of changes in the distribution of workers' characteristics and the returns to those attributes.

First, we find that changes in the distribution of workers' attributes were associated with a shift in density from the lower to upper half of the wage distribution, that is broadly consistent with increasing human capital. These changes are estimated to <u>increase</u> wage inequality, and largely account for the small increase in the upper tail inequality (90-50 difference) over the period. Second, there were substantial increases in wages across the distribution, which we allow for using a combination of the raw median wage change together with changes in the relative returns to attributes. We estimate the change in returns reduced wage inequality slightly, counterbalancing the increase in inequality associated with attribute changes.

Third, we show, visually and analytically, that the minimum wage increases contributed substantially to the wage compression in the lower tail and reduced inequality over the period. The direct effects of the minimum wage increases, associated with moving sub minimum wage workers up to the minimum wage, account for 80-90% of the reduction in the 50-10 difference and about three-quarters of the reduction in the standard deviation of low(wages). These results are broadly consistent with the inequality <u>increasing</u> effects of declining minimum wage in the US context (DiNardo, Fortin, and Lemieux 1996; Fortin, Lemieux, and Lloyd 2021): the former are similar to US estimates in Lee (1999) and Fortin et al. (2021), while the latter are higher than previous international estimates. We document similar relative increases in inequality in male and female wages, but estimate somewhat larger contributions of minimum wage effects of female wages.

Finally, there have been noticeable recent increases in the density of wages between the current minimum and median wages. The increases have been relatively larger for females than males, while a larger fraction of the increase is explained, largely by changes in the returns to worker attributes, for females than for males. We interpret these gender differences as consistent with the recent pay equity settlements contributing to the increases in density in this range. Nonetheless, there remain sizeable residual increases in density in this wage range: allowing minimum wage spillover effects up to 0.125 log-points above the minimum wage can account for much of the residual inequality in the lower tail and standard deviation measures.

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Appendix 1: Distribution regression analysis of spillovers

In this appendix, we describe in more detail how we analysed the presence of possible spillover effects on wages above the minimum wage. To do this, we adapt the distribution regression approach introduced by Foresi and Perrachi (1995), and used by Fortin, Lemieux and Lloyd (2021) (FLL) to parametrise and estimate effects of minimum wages on the wage distribution.[43]

First, as New Zealand has a single national minimum wage, the options for constructing counterfactual distributions are limited.[44] We assume that, in the absence of minimum wage changes, the overall wage distribution is stable around the median, and that the top half of the distribution is unaffected by the minimum wage. This implies that, in the absence of minimum wage changes, there would have been balanced annual wage growth across the distribution, equal to the growth in the median wage. Given the comparatively stable trends for wages in the top half of the distribution, together with the trends for the lower percentiles being consistent with effects of minimum wages over the period that we documented in the previous section, we believe this is a reasonable assumption.

Second, we abstract from possible dis-employment associated with minimum wage increases and allow for three types of minimum wage effects on wages:[45] displacement effects on wages below the minimum wage; an expected mass-point spike in the distribution at the minimum wage; and possible spillover effects on wages above the minimum wage.

In terms of the normalised (to median) wage distribution, our distribution regression approach entails modelling a stable counterfactual cumulative density function (CDF) for wages, together with minimum wage effects relative to year-specific normalised minimum wage, controlling for demographic and other factors that may vary across the distribution.

To implement the distribution regressions, we normalise real wages ($\log(wage_{it})$) relative to the annual median wage ($med_t(\log(wage_{it}))$) from the full sample of workers: $w_{it} = \log(wage_{it}) - med_t(\log(wage_{it}))$. We then divide the normalised w_{it} distribution into

[43] Foresi and Perrachi (1995) developed the distribution regression approach to model the excess stock returns across the distribution of returns. The approach involves estimating a series of binary response models associated with lying above (or below) a distinct set of points of support in the distribution of interest. For example, if $-\infty < y_1 < \cdots < y_J < \infty$ are J points of the the distribution of Y, the the distribution regression approach involves estimating J binary response models for $1(y_i > y_j | x_i), j = 1, \ldots, J$.

[44] In contrast, US research commonly exploits state variation in minimum wages over time. More recently, US (Wiltshire, McPherson, and Reich 2023) and UK (Giupponi et al. 2024) research have used regional variation in relative wages that affect the bite of common minimum wages. Although wages do vary regionally in New Zealand, the variation appears to be relatively small.

[45] Assuming any employment loss is confined to workers with wages below the minimum wage, this will tend to bias upwards the estimated median wage (relative to the true latent distribution) and raise the apparent density of wages below the minimum and lower the density at and above the minimum wage. However, as discussed above, we expect such effects to be relatively minor.

47 intervals:[46] the left tail interval (less than -0.975); 40x0.05 log-point intervals, centred on -0.95, …, 0, … 1.00; a 0.075 log-point interval [1.025,1.10]; 4x0.1 log point intervals centred on 1.15, …, 1.45; and the right tail (above 1.5). This implies 46 cutoffs (w_k) between the intervals,[47] and we estimate the 46 stacked distribution regressions for the binary outcomes $P(w_{it} > w_k|X_{it})$.

In contrast to Foresi and Perrachi, who estimated Logit models, and FLL who estimated Probit models, our analysis is based on linear probability models: this facilitates a simple and direct translation of the estimated parameters from the model in terms of effects of the minimum wage on the CDF of wages, to the fractions of mass missing at various points below the minimum wage, the fraction of excess mass at the minimum wage and, corresponding to spillover effects, the fractions of excess mass at points above the minimum wage. The basic linear probability specification for a cutoff point w_k that we estimate, is:

$$P(w_{it} > w_k|X_{it}) = \alpha_k + X'_{it}\beta$$

where α_k is a intercept associated with the interval cutoff point w_k (i.e. this controls for wage interval-effects, measured relative to year-specific medians), and X_{it} is a vector of worker level control variables that may affect the CDF of wages. These regressions are stacked for each of the k=1, …, 46 cutoff points, and estimated simultaneously to form the distribution regressions. In the stacked regressions, the α_k is a cutoff-*k* fixed effect, and we allow the effects of the controls to evolve smoothly across the distribution: we will return to this issue subsequently.

The control variables include a quadratic in worker's age, and indicator variables for gender, ethnicity (mutually exclusive indicators for Pakeha only, Māori only, Pakeha and Māori, Pacifica, and other ethnicity), and highest qualification (indicators for no qualifications, school, post-school, and degree-level qualifications). Note that the effect of each control variable is the average effect across the distribution: i.e. to shift up or down the estimated CDF by the same amount at each of the cutoff points. More meaningfully, the effects may vary across the distribution – e.g. young workers with lower wages will be concentrated towards the lower end of the distribution, while prime-aged and older workers will be concentrated further up the distribution. A nonparametric way to relax that restriction would be to include a full set of interactions between the control variables and the cutoff points (w_k), however this would require the estimation of a large set of coefficients. More importantly, identification of the

[46] The intervals are chosen based on the mass of the data and but also considering our focus on minimum wage effects, and reflect the right-skewed nature of the log(wage) distribution, which has grown stronger over time partly driven by the increasing minimum wage.
[47] That is, $w_k \in (-0.975, -0.925, \dots, -0.025, 0.025, \dots, 1.025, 1.1, \dots, 1.5)$.

distribution regression relies on the control variable effects changing smoothly across the cutoff points. To allow variation across the distribution and ensure identification, we adopt a parsimonious specification that interacts the controls with a linear specification for w_k, allowing the effects to vary linearly across the distribution.[48] Although potentially restrictive, this approach provides a trade-off between no variation across the distribution and a more flexible specification. In fact, our estimated minimum wage effects of interest are robust to whether the w_k interactions with the controls are included.

Next, we parametrise the minimum wage effects of interest in terms of 0.05 log-point bands around the location of the log(real minimum wage) in each year.[49] We allow for five bands below the minimum wage (centred on -0.25, …, -0.05), a band centred at the minimum, and five bands above the minimum (centred on 0.05, …, 0.3). These effects are parametrised by dummy variables that affect the CDF of interest at points relative to the minimum wage in each year: i.e. we denote dummy variables ($D_{kt}^m = 1[MW_t + M_m \geq w_k], m = -5, \dots, 6$), where M_m represents the relevant band-m boundary (relative to the minimum wage): -0.225, …, -0.025, 0.025, …, 0.275. Including these effects, the stacked distribution regression specification is:

$$P(w_{it} > w_k | X_{it}, D_{mit}) = \alpha_k + X_{it}'\beta + \sum_m \phi_m D_{kt}^m$$

and the minimum wage effects on the pdf in band-*m* relative to the minimum wage can be simply derived as $\delta_m = \phi_m - \phi_{m+1}$.

In order to understand the possible minimum wage effects, consider the stylised example shown in Figure 1, in which directly affected wages are displaced from below the minimum wage to either a spike at the minimum wage or positive spillover effects above the minimum. As a result, the CDF is shifted rightwards at any point affected by the minimum wage (i.e. all log(wages) less than 3.2). That is, $\phi_m > 0$ for all points $M_m < 3.2$; and the shift in the CDF increases below the minimum wage ($\phi_m < \phi_{m+1}, m < 0$), and declines above the minimum wage($\phi_m > \phi_{m+1}, m \geq 0$); implying, $\delta_m < 0$ for $m < 0$, and $\delta_m > 0$ for $m \geq 0$.

Given the pattern of minimum wage increases over the period, we focus on effects within four distinct subperiods (1997-2001, 2002-2008, 2009-2017, and 2018-2023). These subperiods correspond approximately to periods of stable or increasing minimum wages and at different

[48] For example, the effect for each ethnic group at each cutoff point will vary linearly across the distribution. In the case of age, the linear w_k interaction with the quadratic allows a somewhat more flexible response across the distribution.
[49] Over the period, the log-distance between the real minimum wage and median ranges from about -0.65 in the early years to about -0.34 in the later years.

levels.[50] We include fixed effects for each of these four grouped-year periods, and also interact these effects with the relative-to-minimum-wage variables (D_{kt}^{m}). Identification of the minimum wage effect coefficients of interest requires there is sufficient variation in the minimum wage relative to the median over the period. That the minimum varies from about 65 log-points below the median at the start of the period to about 34 log-points below by the end, suggests this will be sufficient.[51]

Finally, recognising that wages may bunch at round dollar values which may affect estimates of minimum wage effects on the CDF at the cutoff points, we also include indicator variables for nominal wages being equal to round dollars between $8 and $25. As wages increase significantly over the period, we allow these effects to vary over time.[52]

We summarise the regression results in Table A1. These results are from a single distribution regression estimated over the full sample period, with controls for worker demographics nominal wages and sub-period effects, and include separate minimum wage effects for each of the four subperiods presented in each column. The top panel presents the minimum wage effect coefficients (ϕ_m) that capture the displacement effects on the CDF at the various points around the minimum wage. We have allowed for effects over a fairly wide range around the minimum wage, but expect the estimates at points closer to the minimum more robustly reflect minimum wage effects than at points further away. Consistent with displacement of wages from below the minimum, for the three points immediately below the minimum wage, the estimates are positive, (mostly) statistically significant, and increase closer to the minimum, over the periods from 2002. In contrast, the effects above the minimum wage are smaller (and negative for the final two subperiods), implying little evidence of spillover effects.[53] Although the estimates at the extremes are typically statistically significant, we suspect they reflect more 'fitting parameters' than robust minimum wage related effects: e.g. the lower end estimates are two positive and two negative providing inconsistent evidence of

[50] Although minimum wage increases started in 2000, and 2001 was also the first year of the youth minimum wage reforms, we include these years in the initial sub-period, because the overall Kaitz index (see Figure 2) and bite of the minimum wage (Figure 4) showed little increase until after 2001. The other periods correspond to, respectively, the minimum wage increases until 2008 of the Labour-led government, the stable minimum wage period of the National-led government, and the increasing minimum wage period of the Labour-led government between 2017 and 2021 (and then maintained level until 2023).

[51] In fact, there is sufficient variation within each of the four subperiods except for 2009-17, during which the minimum wage was closely tied to inflation and nominal wage growth. Although there was some variation in the Kaitz during this period, using 5 log-point intervals relative to the minimum negates this variation.

[52] In particular, we include subsets of the $-value indicators for each sub-period (together with sub-period interactions for $-values that are in more than one sub-period). The choice of which $-values to include was based on a preliminary analysis of bunching in each of the four sub-periods of interest.

[53] Although the estimates are positive and statistically significant for the 1997-2001 and 2002-08 periods, the point estimates are all small (<0.5%), and imply negligible density band effects.

displacement; and while three of four estimates at the higher end are positive (consistent with spillovers), they are each small (0.2-0.3 ppt).

The lower panel of Table A1 presents the implied δ_m minimum wage effects in bands on the pdf, and Figure A3(a) describes these effects graphically. The patterns are broadly consistent with the previous discussion. In particular, there are increasingly strong mass point effects at the minimum wage as the minimum wage increased over the period: from essentially zero over 1997-2001, to 1.7 ppt over 2009-17, and 1.8 ppt over 2018-23; and noticeable wage displacement in the band below the minimum over the latter three period, ranging from -1.5 ppt over 2002-8 to -6.6 ppt over 2018-23. Finally, although not statistically significant, there are possible spillover effects in the two bins above the minimum since 2018.[54]

One concern with this analysis may be that other important secular changes in the wage distribution over the period may affect the robustness of the estimated underlying distribution and subsequent minimum wage related effects. To assess this, we have re-estimated the distribution regressions using the data over the period since 2009, and present the implied minimum wage effects in Figure A3(b) for the 2009-17 and 2018-23 periods. The basic patterns are similar especially over 2018-23: 6.6 ppt displacement in the bin below the minimum, a 1.9 ppt spike at the minimum, and 4.0 ppt and 1.2 ppt spillovers in the two bands above the minimum.

We have also estimated minimum wage effects for various demographic and regional population subgroups, and present the results in Figure A4. For each subgroup we estimate effects from regressions using just that subgroup's wages, but normed relative to the full-sample median wage in each year. The results in panel (a) show comparatively large effects for youth (aged 16-24) compared to adult (25 and over) workers in panel (b), confirming strong and increasing effects on youth wages, consistent with (negative) displacement effects of sub-minimum wages to the minimum wage, and some evidence of spillover effects after 2008. Other than negative displacement immediately below the minimum, the patterns in panel (b) are less systematic and comparatively small for bands away from the minimum wage, consistent with the notion that minimum wages have less impact on adult wages.

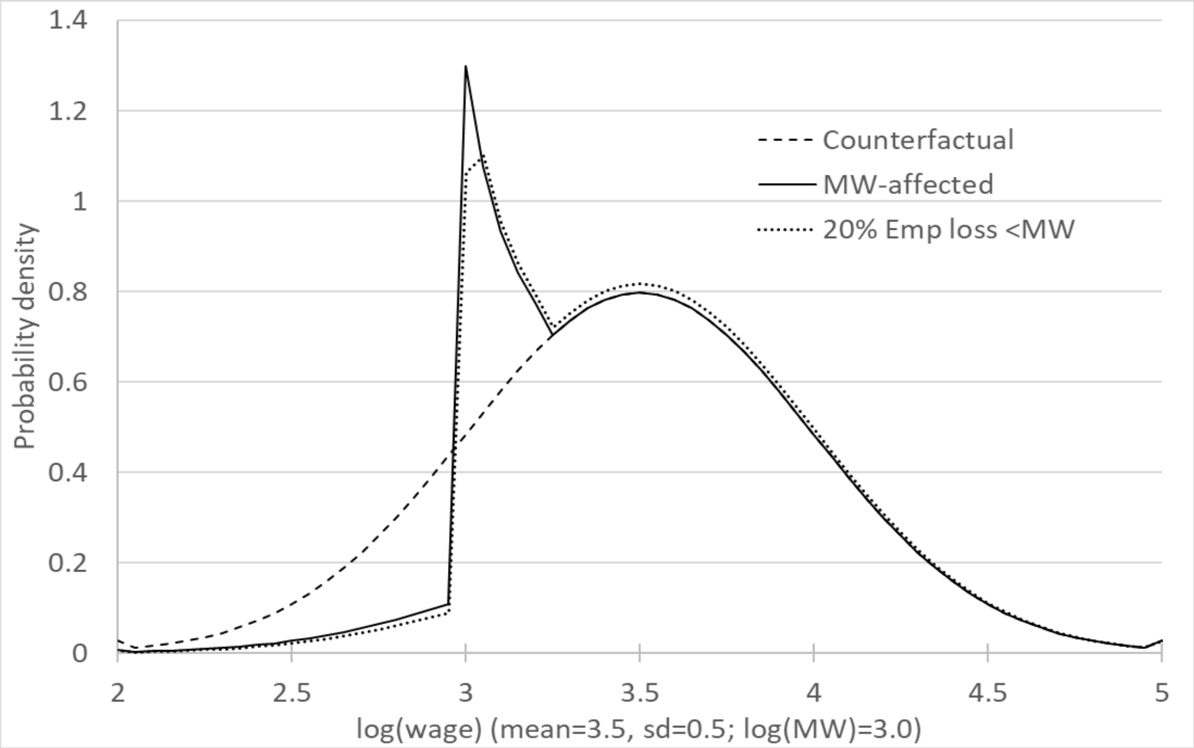
The effects for male and female workers shown in panels (c) and (d), show stronger effects for females, in terms of the displacement of sub-minimum wages, the mass around the

[54] Although the point estimates away from the minimum wage are rarely statistically significant, 11 of the 12 estimates in the three bands below the minimum are negative (and 4 are statistically significant); while only 5 of the 12 estimates in the three bands above the minimum are positive, and 3 of the 4 significant estimates are negative.

minimum and spillovers above the minimum wage. Finally, we compare estimates for the main centres (Auckland, Wellington and Canterbury regional councils) versus other areas in panels (e) and (f). The effects are quite similar, although show somewhat stronger displacement below the minimum for workers outside the main centres: e.g. in 2018-23, there was a 7.3 ppt mass displacement below the minimum wage, compared to 6.2 ppt in the main centres.

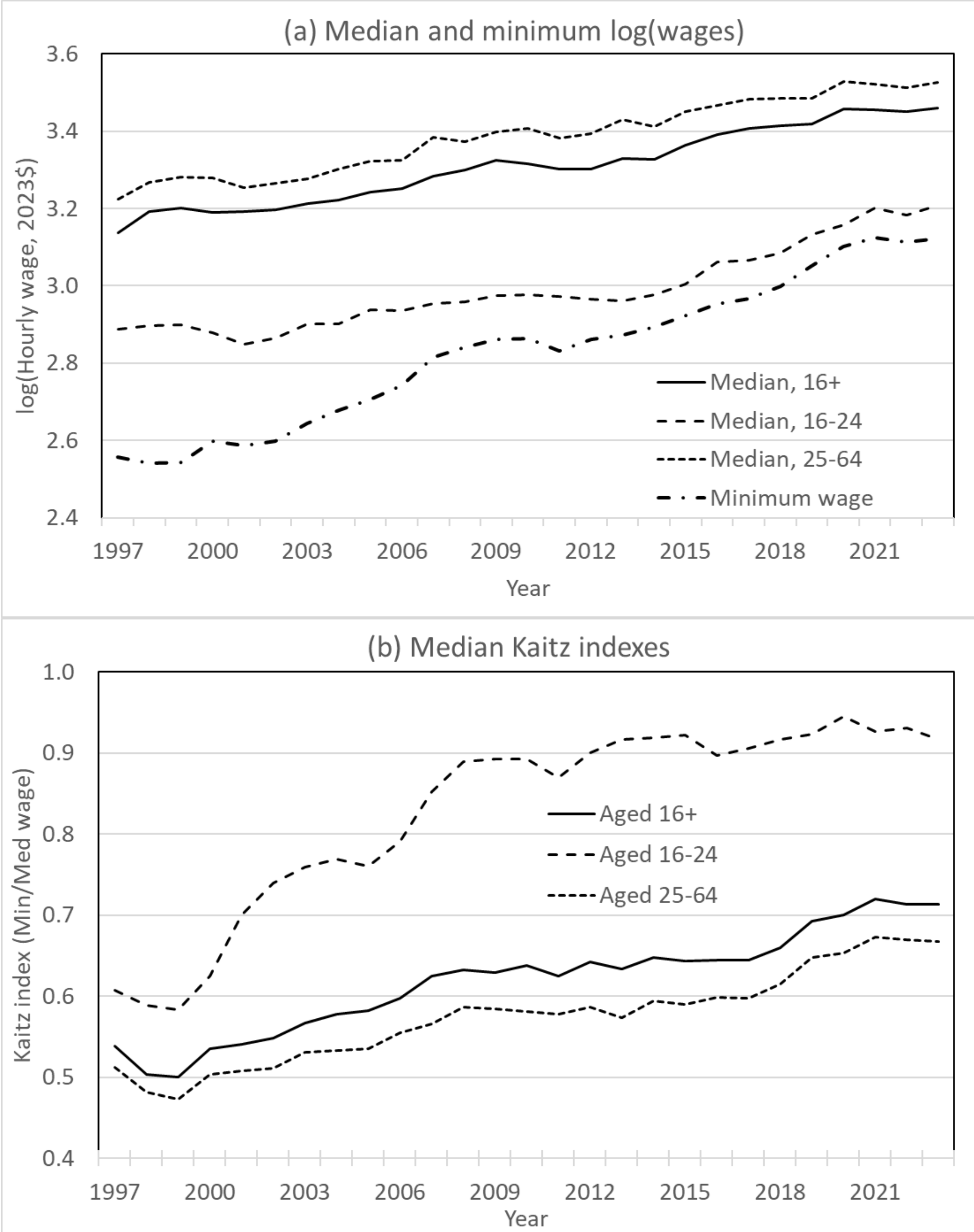
Although the estimates are somewhat variable, we believe they provide support for the existence of some spillover effects in the 1-2 bins (up to 0.125 log-points) above the minimum wage in the most recent (2018-2023) period.

Figure 1: Stylised example of minimum wage effects on wage distribution



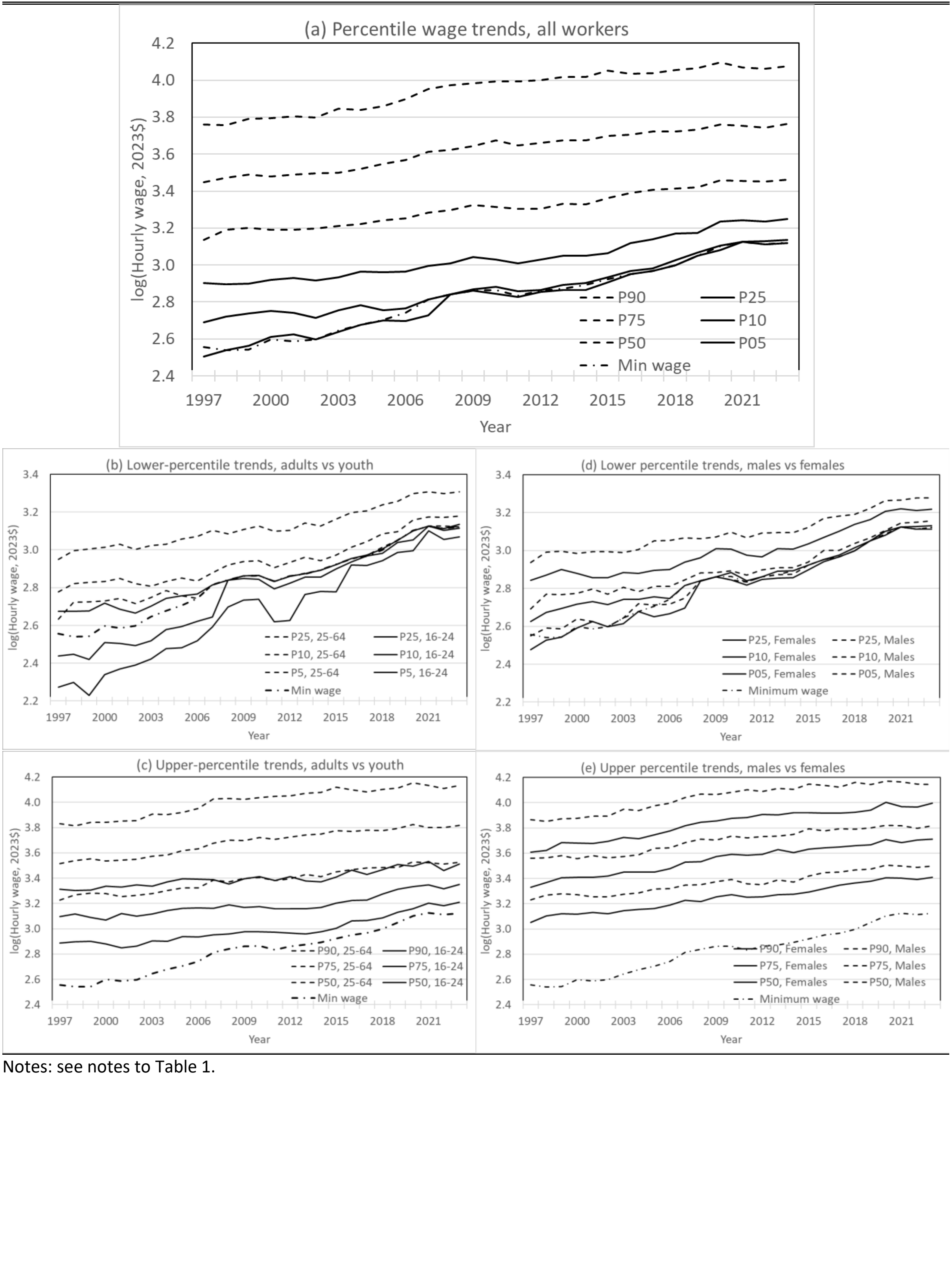
Notes: The figure describes the minimum wage effects on the distribution of log(wages): in the absence of a minimum wage (dashed line), with a minimum wage but no employment loss (solid line), and with employment loss of directly affected workers (below the minimum wage). In the solid line, we assume the minimum wage is binding on 75% of wages below the minimum; of the cumulative affected sub-minimum wages, 40% are moved to the minimum and the remaining 60% (spillovers) are distributed over the 0.20 log-points above the minimum; in the dotted line, we also assume there is 20% employment loss of workers below the minimum wage, and with resulting lost density redistributed above the minimum wage.

Figure 2: Real wage and minimum wage trends



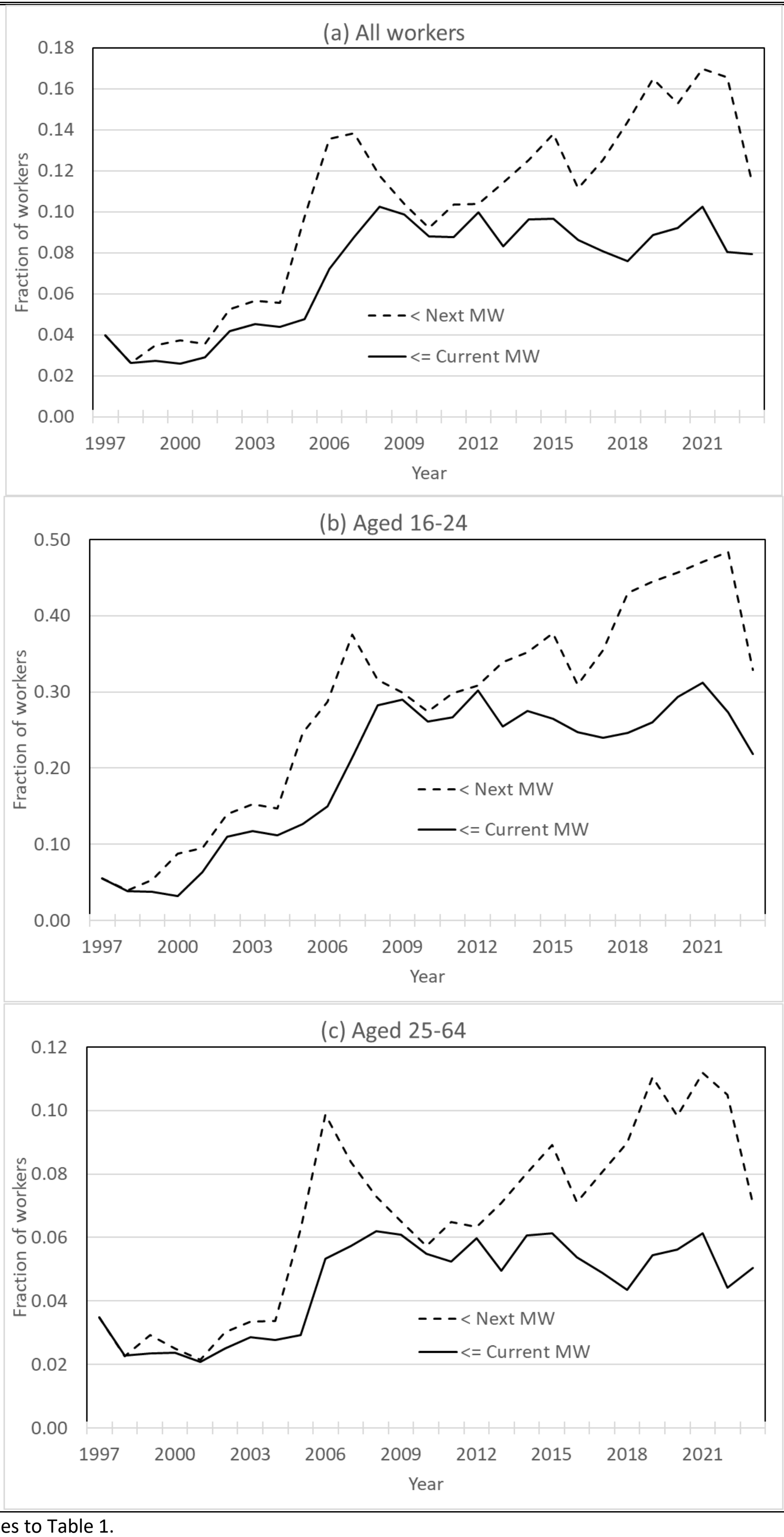
Notes: All wage estimates are based on reported or derived hourly wages for wage and salary employees, deflated by the CPI to 2023-$ values, and are weighted by the HLFS survey final-weights. The Kaitz indexes are estimated as the median person-specific Kaitz ratio (i.e. calculated as the ratio of the minimum wage they face to their wage).

Figure 3: Percentile wage trends



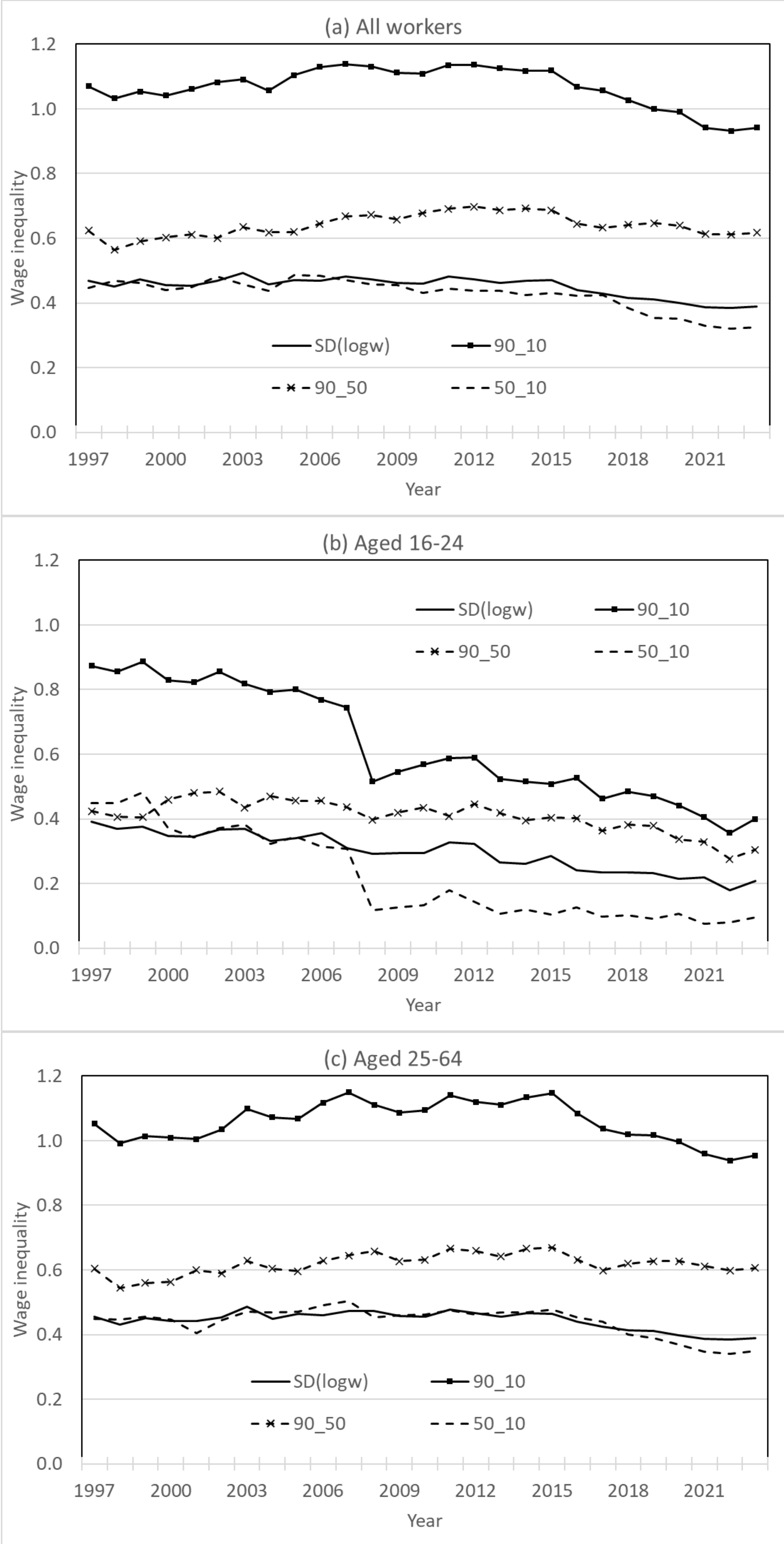
Notes: see notes to Table 1.

Figure 4: Minimum wage bite



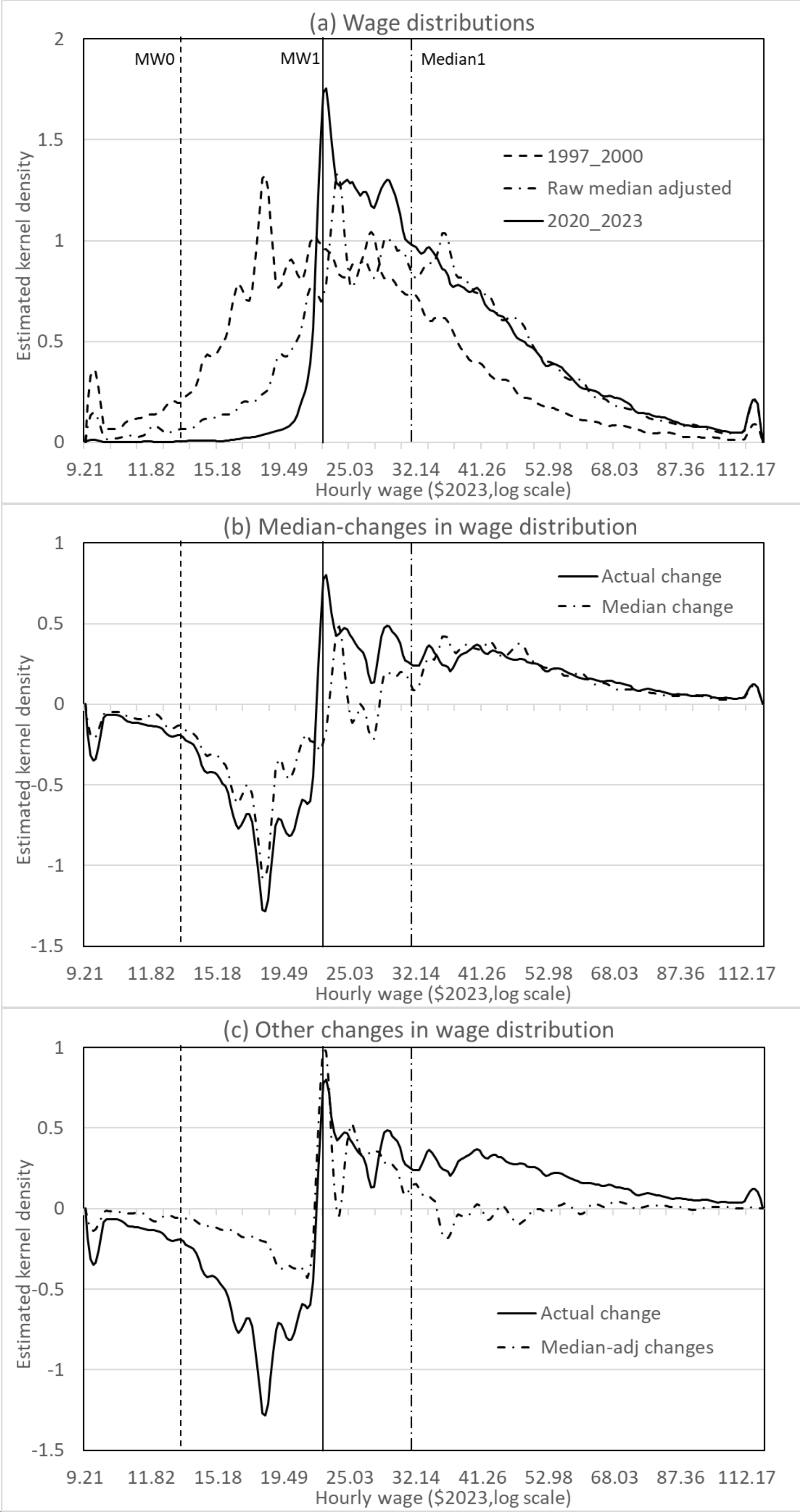
Notes: see notes to Table 1.

Figure 5: Wage inequality



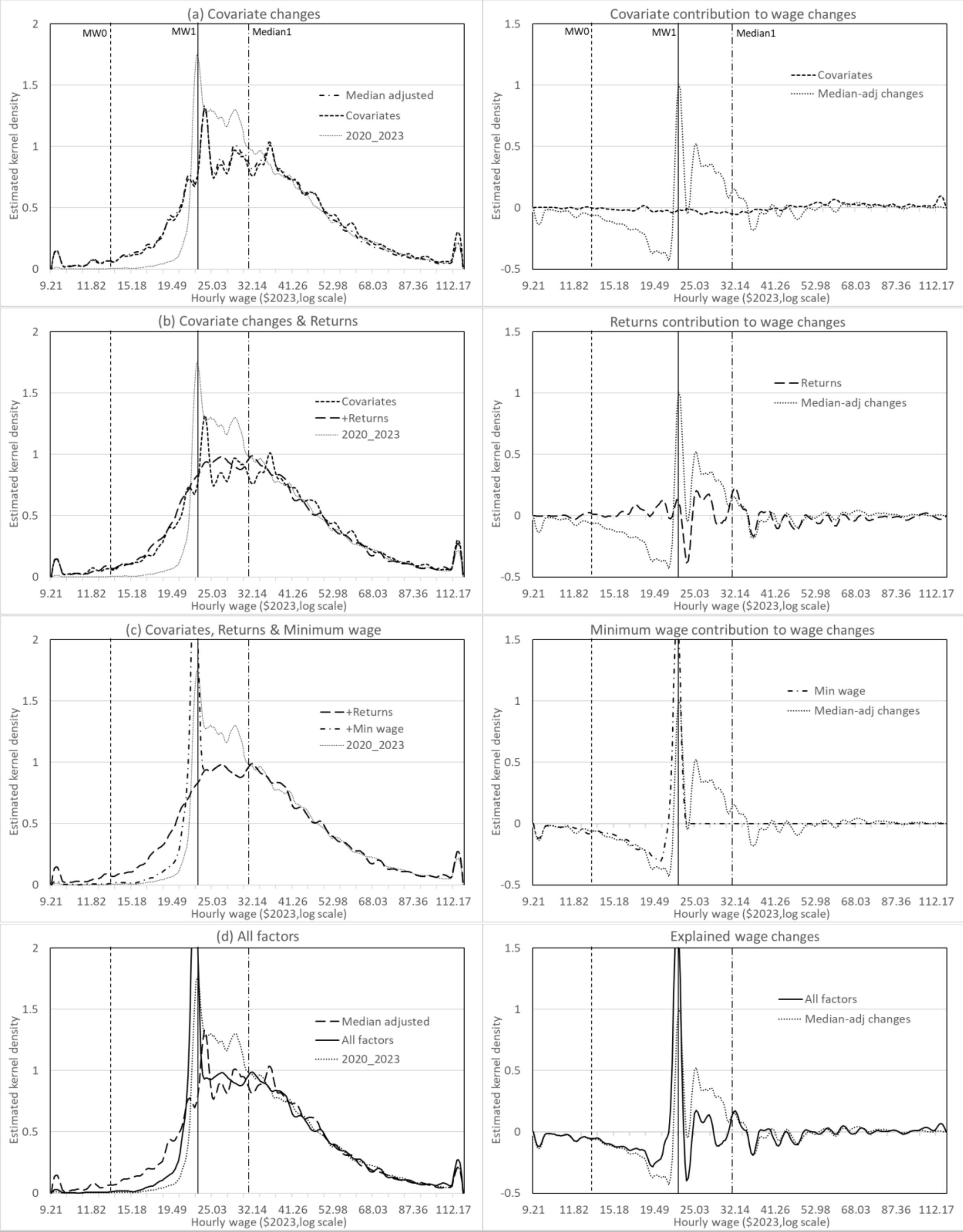
Notes: see notes to Table 1. Real hourly wages have been trimmed at $2.50 and $250 (2023-$) to reduce the influence of outliers on the standard deviation in this figure.

Figure 6: Wage distribution changes, 1997-2000 and 2020-2023



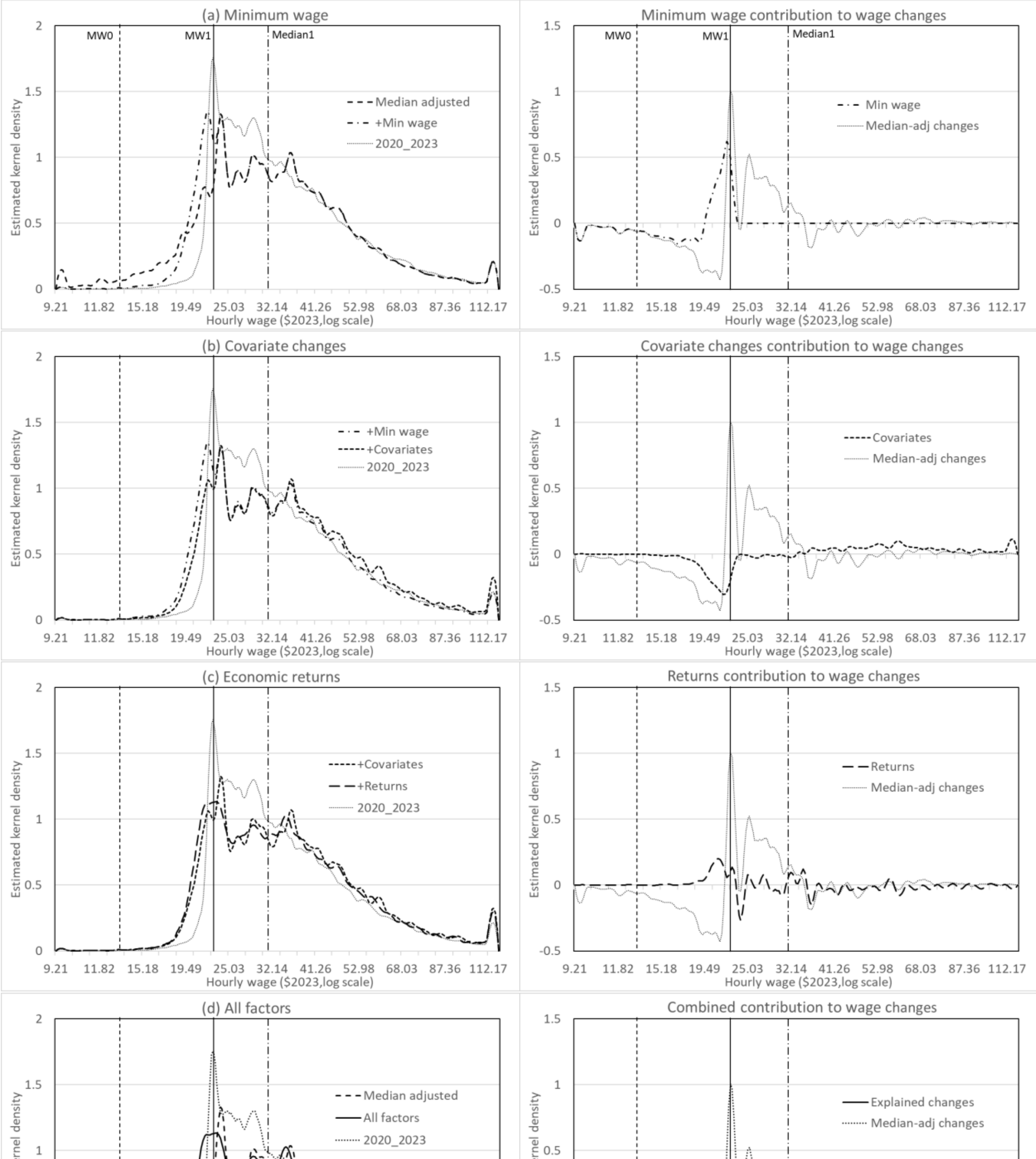
Notes: The kernel density estimates of log(wage) (left- and right-censored at 2.25 and 4.75) are weighted using HLFS sampling weights, and use an Epanechikov kernel with a bandwidth of 0.01 at 0.01 log-interval evaluation points between 2.22 and 4.78. We then present MA(5) smoothed figures.

Figure 7: Contributions to the wage distribution changes



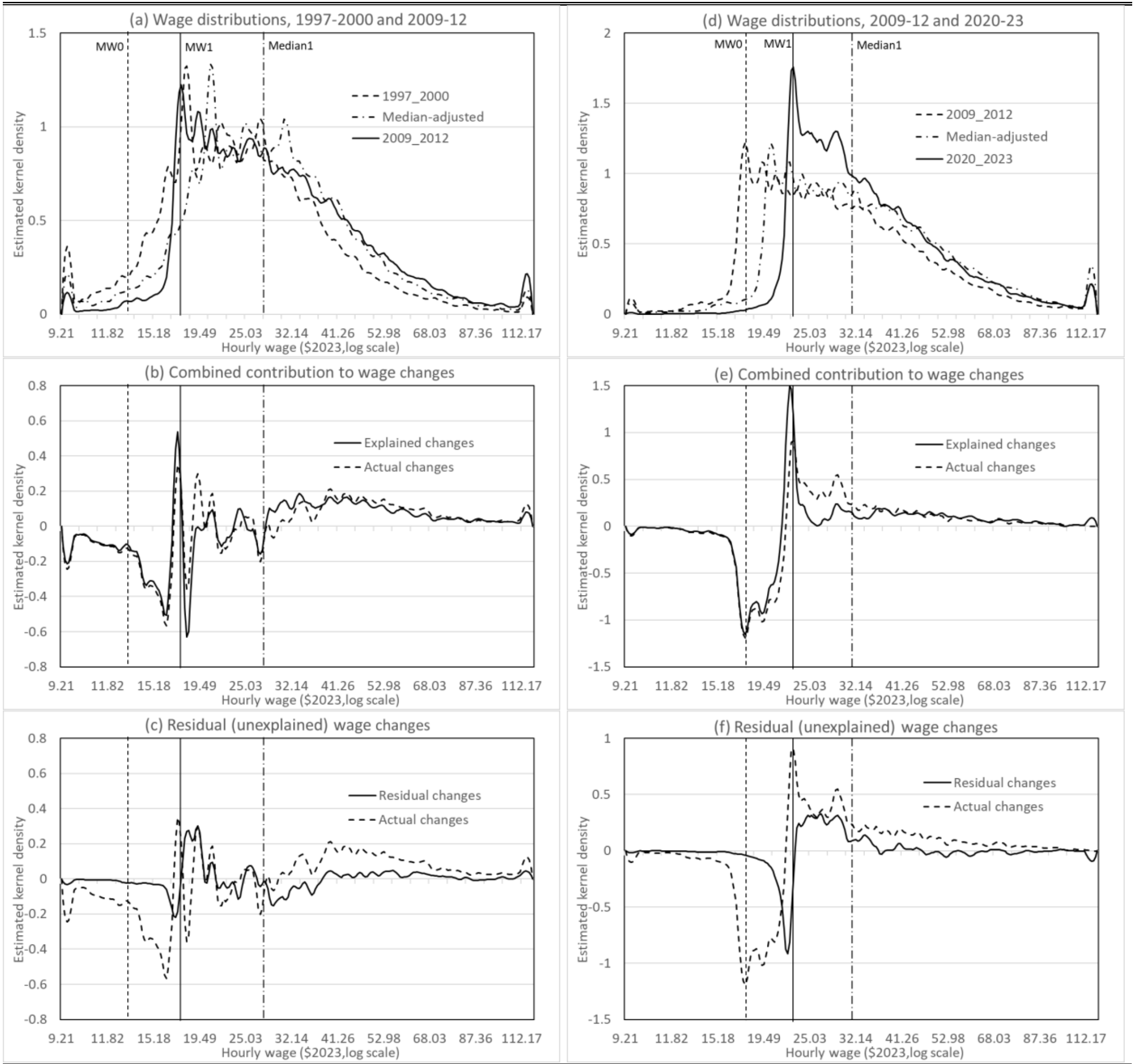
Notes: see notes to Figure 6.

Figure 8: Alternative sequence to wage distribution changes



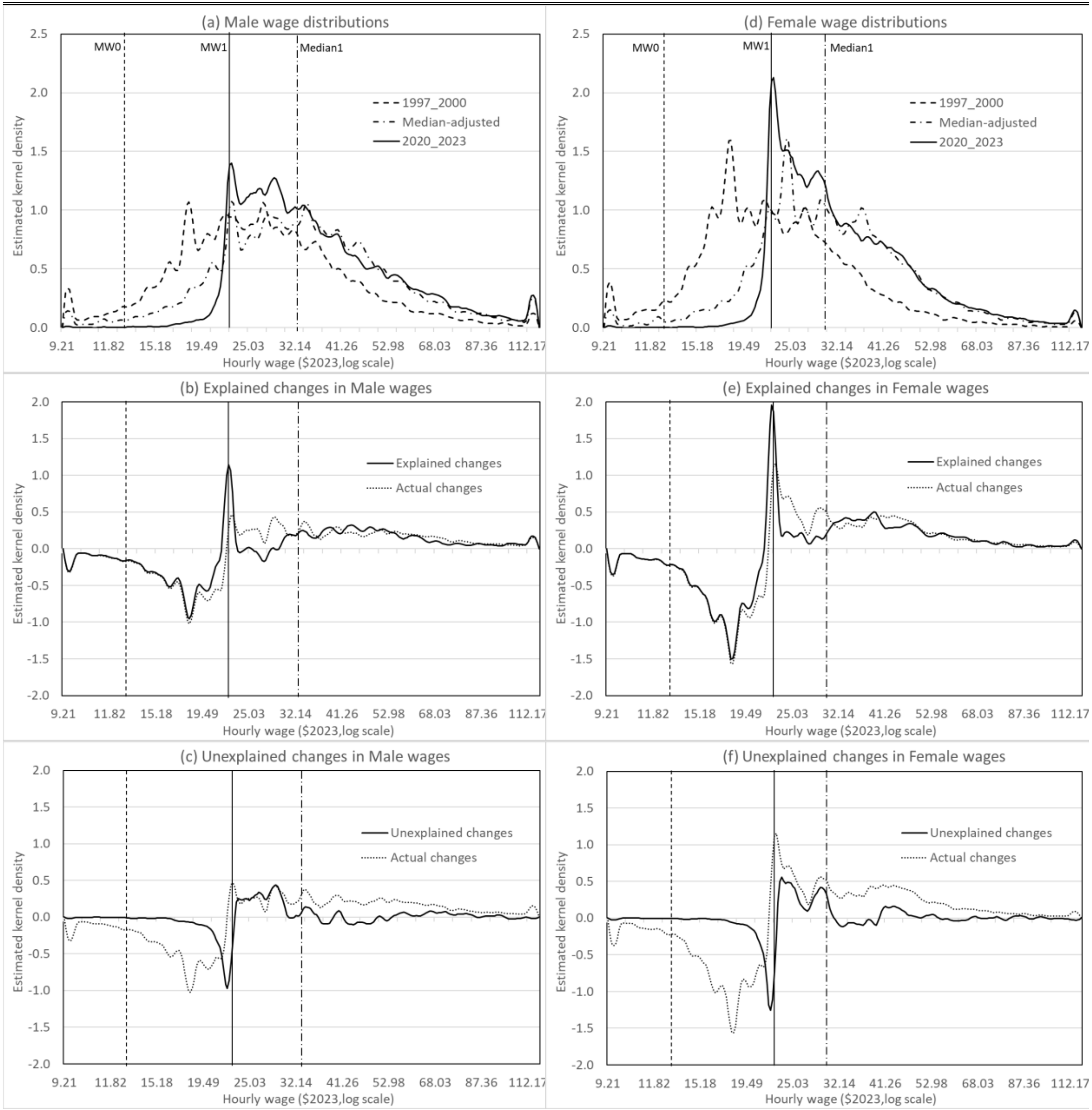
Notes: see notes to Figure 6.

Figure 9: Subperiod wage distribution changes, 1997-2000 to 2009-12 and 2009-12 to 2020-23



Notes: see notes to Figure 6.

Figure 10: Contributions to Male and Female wage distribution changes



Notes: see notes to Figure 6.

Table 1: Descriptive sample statistics

	All workers			Min Wage affected workers[(1)]	
	All years	2000	2023	2000	2023
W&S Employed	0.523	0.479	0.547	1	1
Conditional on W&S employed:					
Female	0.489	0.489	0.489	0.541	0.574
Aged 16-17	0.025	0.033	0.024	0.115	0.120
18-19	0.033	0.036	0.029	0.184	0.118
20-24	0.108	0.111	0.102	0.127	0.186
25-64	0.801	0.809	0.793	0.547	0.516
65+	0.033	0.011	0.052	0.029	0.061
European/Pakeha	0.749	0.813	0.664	0.781	0.604
Māori	0.132	0.127	0.151	0.188	0.195
Pacifica	0.057	0.050	0.070	0.053	0.100
Other ethnicity	0.132	0.054	0.211	0.045	0.224
No quals	0.151	0.192	0.101	0.297	0.170
School quals	0.267	0.266	0.281	0.352	0.473
Post-school qual	0.290	0.330	0.237	0.225	0.184
Degree quals	0.281	0.209	0.358	0.113	0.143
Main centres[(2)]	0.592	0.581	0.599	0.453	0.539
Wage	33.17	28.48	37.76	10.62	22.22
	(20.0)	(18.8)	(19.3)	(2.7)	(2.1)
Log(wage)	3.383	3.230	3.544	2.316	3.094
	(0.46)	(0.46)	(0.39)	(0.34)	(0.13)
Wage ≤ Min wage	0.074	0.026	0.079	0.695	0.533
Wage < Next MW	0.108	0.037	0.115	1	1
No. W&S obs	384,612	12,564	15,489	498	2,319
W&S pop	47,705,300	1,375,300	2,252,300	51,200	335,200
No. person obs	759,768	26,946	28,569	498	2,319
Person pop	91,234,200	2,874,100	4,115,700	51,200	335,200

Notes: Sample counts have been randomly rounded to base-3; population counts have been round to the nearest 100. All estimates are weighted by the HLFS sample weights, and calculated using the rounded population counts. The wage and salary employed rate is calculated as the W&S pop/Person pop (both aged 16 and over). All other statistics are based on W&S employed population. Ethnicity rates are based on full ethnicity reports and sum to more than 1. Wages are expressed in 2023-$ values, and have been censored at $2.50 and $250 to reduce to influence of outliers; standard deviations of wages and log(wages) are in parentheses.

(1) We define potentially affected workers as those with wages less than the next year's minimum wage.

(2) Main centres are defined as respondent who live in the Auckland, Wellington and Canterbury Regional Council areas.

Table 2: Wage trend summary

	Changes over period					Annual
	1997-2001	2001-08	2008-17	2017-23	1997-2023	Average
Minimum wage	0.030	0.253	0.127	0.155	0.566	0.022
All workers:						
Kaitz (median)	0.002	0.092	0.012	0.069	0.175	0.007
Average wage	0.053	0.126	0.110	0.077	0.366	0.014
P95	0.008	0.238	0.052	0.013	0.295	0.011
P90	0.043	0.167	0.083	0.038	0.317	0.012
P75	0.043	0.133	0.101	0.041	0.318	0.012
Median (P50)	0.055	0.107	0.115	0.054	0.324	0.012
P25	0.030	0.077	0.162	0.111	0.349	0.013
P10	0.053	0.097	0.187	0.153	0.445	0.017
P5	0.120	0.215	0.158	0.152	0.614	0.024
≤Min wage	-0.011	0.074	-0.022	-0.001	0.039	0.002
<Next Min wage	-0.004	0.082	0.008	-0.011	0.075	0.003
SD(log(wages))	-0.015	0.018	-0.043	-0.039	-0.079	-0.003
P90-P10	-0.009	0.070	-0.074	-0.115	-0.129	-0.005
P90-P50	-0.012	0.061	-0.040	-0.016	-0.007	0.000
P50-P10	0.003	0.010	-0.034	-0.099	-0.121	-0.005
Youth workers:						
Kaitz (median)	0.092	0.189	0.017	0.011	0.310	0.012
Average wage	0.032	0.128	0.090	0.132	0.383	0.015
P95	-0.021	0.044	0.045	0.082	0.150	0.006
P90	0.016	0.027	0.074	0.084	0.201	0.008
P75	0.025	0.068	0.038	0.123	0.254	0.010
Median (P50)	-0.040	0.110	0.108	0.143	0.321	0.012
P25	0.012	0.154	0.133	0.162	0.462	0.018
P10	0.067	0.334	0.127	0.146	0.675	0.026
P5	0.098	0.327	0.221	0.150	0.795	0.031
≤Min wage	0.009	0.219	-0.043	-0.022	0.163	0.006
<Next Min wage	0.040	0.221	0.039	-0.026	0.274	0.011
SD(log(wages))	-0.047	-0.053	-0.058	-0.027	-0.185	-0.007
P90-P10	-0.051	-0.307	-0.053	-0.062	-0.474	-0.018
P90-P50	0.056	-0.082	-0.034	-0.059	-0.120	-0.005
P50-P10	-0.107	-0.225	-0.019	-0.003	-0.354	-0.014
Adult workers:						
Kaitz (median)	-0.005	0.080	0.010	0.070	0.155	0.006
Average wage	0.050	0.125	0.102	0.068	0.346	0.013
P95	0.007	0.263	-0.001	0.037	0.305	0.012
P90	0.023	0.178	0.050	0.052	0.303	0.012
P75	0.028	0.160	0.078	0.040	0.305	0.012
Median (P50)	0.029	0.119	0.110	0.044	0.301	0.012
P25	0.079	0.056	0.120	0.102	0.357	0.014
P10	0.071	0.072	0.123	0.135	0.401	0.015
P5	0.109	0.097	0.130	0.152	0.489	0.019
≤Min wage	-0.014	0.041	-0.013	0.001	0.016	0.001
<Next Min wage	-0.013	0.051	0.008	-0.010	0.036	0.001
SD(log(wages))	-0.012	0.030	-0.048	-0.035	-0.065	-0.002
P90-P10	-0.047	0.106	-0.073	-0.083	-0.098	-0.004
P90-P50	-0.005	0.059	-0.060	0.008	0.002	0.000
P50-P10	-0.042	0.047	-0.014	-0.091	-0.099	-0.004

Notes: All variables are measured in logs, except the Kaitz index, and ≤Minimum wage and <Next Minimum wage which are fractions.

Table 3: Decomposition of change in inequality, from 1997-2000 to 2020-2023

	Measure of inequality				
	90–10	90–50	50–10	SD	Gini
1997-2000	1.058	0.596	0.463	0.464	0.263
2020-2023	0.951	0.620	0.331	0.390	0.234
Total change	-0.107	0.024	-0.132	-0.074	-0.029
	[-10.1%]	[4.1%]	[-28.5%]	[-15.9%]	[-11.0%]
Contributions from:					
Covariates	0.047	0.031	0.016	0.026	0.016
	[-44%]	[128%]	[-12%]	[-36%]	[-56%]
Returns	-0.011	-0.002	-0.009	-0.008	-0.003
	[10%]	[-9%]	[7%]	[11%]	[12%]
Minimum wage	-0.117	0.000	-0.117	-0.053	-0.017
	[109%]	[0%]	[89%]	[72%]	[58%]
Total explained	-0.081	0.029	-0.110	-0.035	-0.004
	[75%]	[119%]	[83%]	[48%]	[13%]
Residual	*-0.026*	*-0.005*	*-0.022*	*-0.038*	*-0.025*
	[25%]	*[-19%]*	*[17%]*	*[52%]*	*[87%]*
Spillovers to	*-0.024*	*0.000*	*-0.024*	*-0.015*	*-0.007*
0.125 log-pts	*[22%]*	*[0%]*	*[18%]*	*[20%]*	*[24%]*
Spillovers to	*-0.001*	*0.000*	*-0.001*	*-0.008*	*-0.005*
Median	*[1%]*	*[0%]*	*[1%]*	*[12%]*	*[18%]*
Alternative sequence:					
Minimum wage	-0.071	0.000	-0.071	-0.049	-0.014
	[66%]	[0]	[54%]	[66%]	[47%]
Covariates	0.055	0.021	0.034	0.021	0.013
	[-51%]	[87%]	[-26%]	[-28%]	[-46%]
Returns	-0.005	-0.004	-0.002	-0.001	-0.001
	[5%]	[-15%]	[1%]	[2%]	[2%]
Total explained	-0.021	0.018	-0.039	-0.029	-0.001
	[20%]	[72%]	[30%]	[40%]	[3%]
Alternative sequence (based on relative rank replacement of lower tail wages):					
Minimum wage	-0.108	0.000	-0.108	-0.053	-0.017
	[100%]	[0%]	[82%]	[72%]	[58%]
Covariates	0.059	0.031	0.028	0.029	0.017
	[-55%]	[128%]	[-21%]	[-39%]	[-60%]
Returns	-0.003	-0.002	0.000	-0.008	-0.004
	[2%]	[-9%]	[0%]	[11%]	[12%]
Total explained	-0.051	0.029	-0.080	-0.032	-0.003
	[48%]	[119%]	[61%]	[44%]	[10%]

Notes: Entries (%) in square brackets are the relative change in inequality (in the third row), and the relative contribution to the total change (in subsequent rows).

Table 4: Decomposition of subperiod changes in inequality

	Measure of inequality				
	90–10	90–50	50–10	SD	Gini
1997_2000	1.058	0.596	0.463	0.464	0.263
2009_2012	1.113	0.669	0.444	0.470	0.278
2020_2023	0.951	0.620	0.331	0.390	0.234
	(a) 1997_2000 to 2009_2012				
Total change	0.055	0.074	-0.019	0.006	0.015
	[5.2%]	[12.4%]	[-4.0%]	[1.3%]	[5.8%]
Covariates	0.023	0.012	0.012	0.014	0.009
	[42%]	[16%]	[-63%]	[245%]	[58%]
Returns	0.047	0.025	0.022	0.012	0.007
	[86%]	[34%]	[-118%]	[199%]	[48%]
Minimum wage	-0.043	0.000	-0.043	-0.027	-0.007
	[-77%]	[0%]	[230%]	[-449%]	[-48%]
Residual	0.027	0.037	-0.009	0.006	0.007
	[49%]	[50%]	[51%]	[105%]	[43%]
Spillovers to	*-0.009*	*0.000*	*-0.009*	*-0.010*	*-0.003*
0.125 log-pts	*[-17%]*	*[0%]*	*[51%]*	*[-171%]*	*[-22%]*
Spillovers to	*0.000*	*0.000*	*0.000*	*0.001*	*0.000*
median	*[0%]*	*[0%]*	*[0%]*	*[21%]*	*[2%]*
	(b) 2009_2012 to 2020_2023				
Total change	-0.162	-0.049	-0.113	-0.079	-0.044
	[-14.6%]	[-7.3%]	[-25.5%]	[-16.9%]	[-15.9%]
Covariates	0.013	0.011	0.002	0.002	0.002
	[-8%]	[-23%]	[-2%]	[-3%]	[-4%]
Returns	-0.078	-0.027	-0.051	-0.020	-0.012
	[48%]	[55%]	[45%]	[25%]	[28%]
Minimum wage	-0.046	0.000	-0.046	-0.019	-0.007
	[28%]	[0%]	[40%]	[24%]	[15%]
Residual	-0.052	-0.033	-0.019	-0.043	-0.027
	[32%]	[68%]	[17%]	[54%]	[62%]
Spillovers to	*-0.024*	*0.000*	*-0.024*	*-0.013*	*-0.006*
0.125 log-pts	*[15%]*	*[0%]*	*[21%]*	*[16%]*	*[14%]*
Spillovers to	*-0.001*	*-0.001*	*0.000*	*-0.008*	*-0.005*
Median	*[1%]*	*[3%]*	*[0%]*	*[10%]*	*[11%]*

Notes: Entries (%) in square brackets are the relative change in inequality (in the top row of each panel), and the relative contribution to the total change (in subsequent rows).

Table 5: Decomposition of changes in Male and Female wage inequality

	Male wages					Female wages				
	90-10	90-50	50-10	SD	Gini	90-10	90-50	50-10	SD	Gini
1997-2000	1.119	0.606	0.513	0.482	0.271	0.959	0.551	0.408	0.431	0.242
2009-2012	1.196	0.717	0.479	0.492	0.291	1.013	0.623	0.390	0.437	0.257
2020-2023	1.018	0.658	0.361	0.410	0.246	0.855	0.576	0.278	0.363	0.216
(a) 1997-2000 to 2020-2023 changes										
Total change	-0.101	0.052	-0.153	-0.072	-0.026	-0.105	0.025	-0.130	-0.068	-0.026
	[-9.0%]	[8.6%]	[-29.7%]	[-14.9%]	[-9.5%]	[-10.9%]	[4.5%]	[-31.8%]	[-15.7%]	[-10.7%]
Contributions from:										
Covariates	0.011	0.020	-0.009	0.018	0.011	0.069	0.042	0.027	0.020	0.014
	[-11%]	[38%]	[6%]	[-26%]	[-43%]	[-66%]	[170%]	[-21%]	[-30%]	[-54%]
Returns	-0.011	-0.003	-0.008	-0.008	-0.004	-0.009	-0.004	-0.005	-0.007	-0.003
	[11%]	[-6%]	[6%]	[12%]	[15%]	[8%]	[-15%]	[4%]	[10%]	[10%]
Minimum wage	-0.109	0.000	-0.109	-0.053	-0.015	-0.131	0.000	-0.131	-0.052	-0.019
	[109%]	[0%]	[72%]	[74%]	[59%]	[125%]	[0%]	[101%]	[77%]	[73%]
Residual	0.009	0.035	-0.026	-0.029	-0.018	-0.034	-0.014	-0.020	-0.029	-0.019
	[-9%]	[68%]	[17%]	[40%]	[70%]	[32%]	[-55%]	[16%]	[43%]	[72%]
(b) 2009-2012 to 2020-2023 changes										
Total change	-0.178	-0.060	-0.119	-0.082	-0.045	-0.158	-0.047	-0.111	-0.074	-0.041
	[-14.9%]	[-8.3%]	[-24.8%]	[-16.7%]	[-15.6%]	[-15.6%]	[-7.5%]	[-28.5%]	[-17.0%]	[-15.8%]
Contributions from:										
Covariates	0.006	0.014	-0.008	0.002	0.002	0.022	0.005	0.016	0.002	0.001
	[-3%]	[-24%]	[7%]	[-2%]	[-4%]	[-14%]	[-11%]	[-15%]	[-3%]	[-2%]
Returns	-0.087	-0.040	-0.048	-0.023	-0.014	-0.105	-0.051	-0.054	-0.032	-0.020
	[49%]	[66%]	[40%]	[28%]	[31%]	[66%]	[108%]	[49%]	[43%]	[49%]
Minimum wage	-0.027	0.000	-0.027	-0.016	-0.005	-0.054	0.000	-0.054	-0.023	-0.009
	[15%]	[0%]	[23%]	[20%]	[10%]	[34%]	[0%]	[49%]	[32%]	[21%]
Residual	-0.069	-0.034	-0.035	-0.045	-0.029	-0.021	-0.002	-0.019	-0.021	-0.013
	[39%]	[57%]	[30%]	[55%]	[63%]	[13%]	[3%]	[17%]	[28%]	[32%]

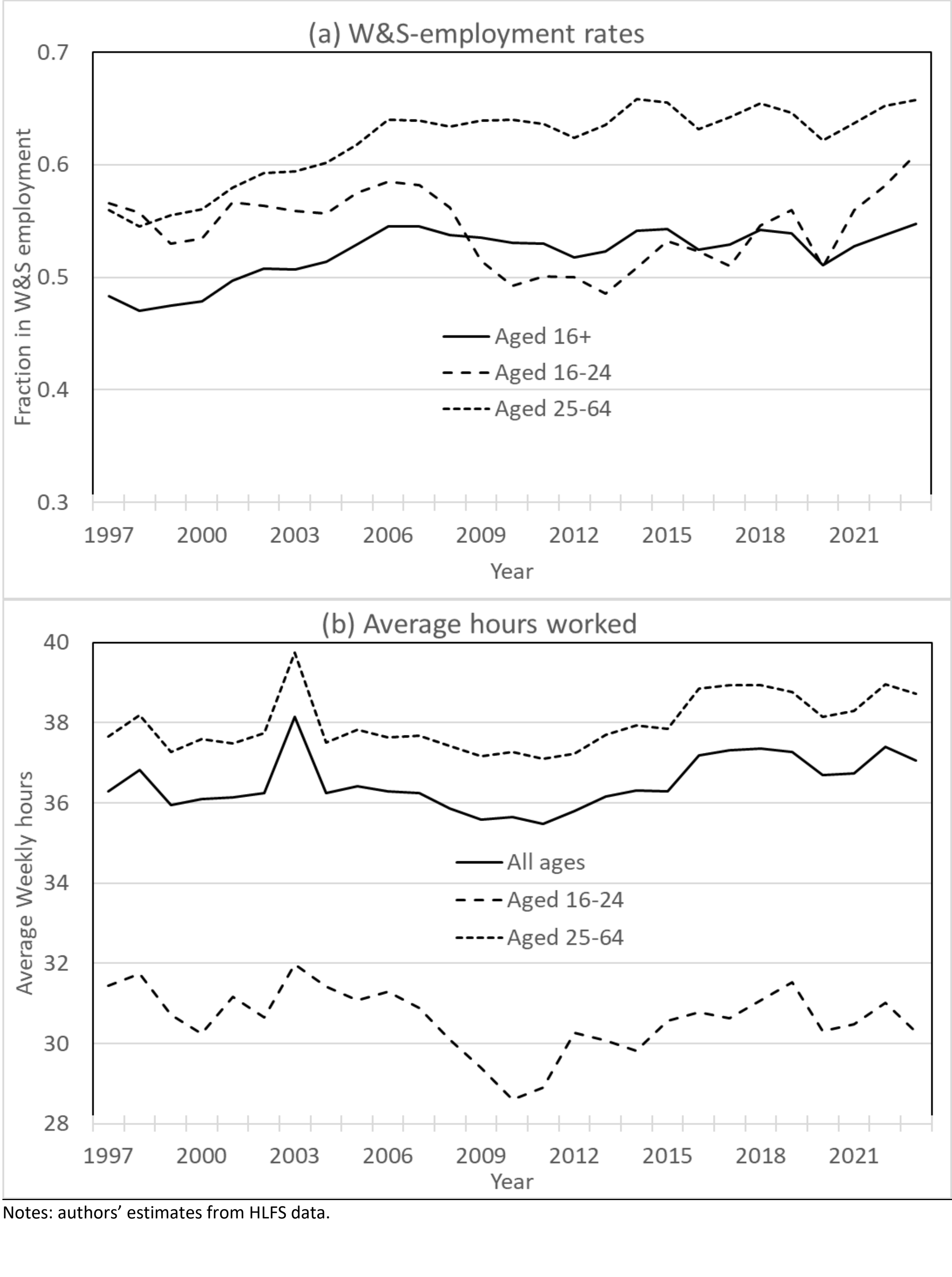
Notes: Entries (%) in square brackets are the relative change in inequality (in the top row of each panel), and the contribution to the total change (in subsequent rows).

Table A1: Estimated minimum wage effects on wage distribution

CDF coefficients (ϕ_m):	1997-2001	2002-08	2009-17	2018-23
1(wit>MWt-0.275)	0.005***	0.005***	0.003**	-0.008*
	(0.001	(0.001)	(0.001)	(0.004)
1(wit>MWt-0.225)	0.002***	0.0045***	-0.001	-0.006
	(0.0003)	(0.001)	(0.001)	(0.004)
1(wit>MWt-0.175)	0.003***	0.004***	-0.003	-0.015***
	(0.001)	(0.001)	(0.003)	(0.004)
1(wit>MWt-0.125)	0.005***	0.003	-0.003	-0.025***
	(0.001)	(0.002)	(0.005)	(0.005)
1(wit>MWt-0.075)	0.005***	0.002	-0.008*	-0.023***
	(0.001)	(0.004)	(0.004)	(0.007)
1(wit>MWt-0.025)	0.004*	0.017**	0.031***	0.043***
	(0.003)	(0.006)	(0.005)	(0.007)
1(wit>MWt+0.025)	0.006	0.011*	0.014*	0.025***
	(0.004)	(0.006)	(0.007)	(0.007)
1(wit>MWt+0.075)	-0.002	0.004	0.015**	0.011*
	(0.004)	(0.005)	(0.007)	(0.006)
1(wit>MWt+0.125)	-0.003	-0.0008	0.0003	0.004
	(0.005)	(0.007)	(0.007)	(0.004)
1(wit>MWt+0.175)	-0.009	0.002	-0.001	0.010*
	(0.006)	(0.007)	(0.005)	(0.005)
1(wit>MWt+0.225)	0.007	-0.004	-0.003	0.016***
	(0.007)	(0.005)	(0.004)	(0.004)
1(wit>MWt+0.275)	0.006	-0.011**	-0.017***	0.021***
	(0.010)	(0.004)	(0.004)	(0.005)
Implied density bands effects, relative to minimum wage ($\delta_m = \phi_m - \phi_{m+1}$):				
-0.25+/--0.025	0.002***	0.001	0.004***	-0.002
	(0.001)	(0.001)	(0.001)	(0.003)
-0.20+/--0.025	-0.001	0.0003	0.003	0.009***
	(0.001)	(0.001)	(0.003)	(0.003)
-0.15+/--0.025	-0.002*	0.002	0.0001	0.010**
	(0.001)	(0.001)	(0.003)	(0.004)
-0.10+/--0.025	0.0003	0.0004	0.004	-0.002
	(0.001)	(0.004)	(0.003)	(0.003)
-0.05+/--0.025	0.0005	-0.015**	-0.039***	-0.066***
	(0.002)	(0.007)	(0.005)	(0.006)
MW+/--0.025	-0.002	0.006	0.017**	0.018*
	(0.004)	(0.005)	(0.006)	(0.010)
0.05+/--0.025	0.008***	0.008	-0.001	0.015
	(0.003)	(0.007)	(0.009)	(0.010)
0.10+/--0.025	0.002	0.004	0.015	0.007
	(0.005)	(0.008)	(0.009)	(0.007)
0.15+/--0.025	0.006	-0.002	0.001	-0.006
	(0.006)	(0.008)	(0.010)	(0.005)
0.20+/--0.025	-0.016**	0.006	0.002	-0.006
	(0.007)	(0.008)	(0.007)	(0.007)
0.25+/--0.025	0.0006	0.006	0.014**	-0.005
	(0.012)	(0.007)	(0.006)	(0.008)
0.30+/--0.025	0.006	-0.011**	-0.017***	0.021***
	(0.010)	(0.004)	(0.004)	(0.005)

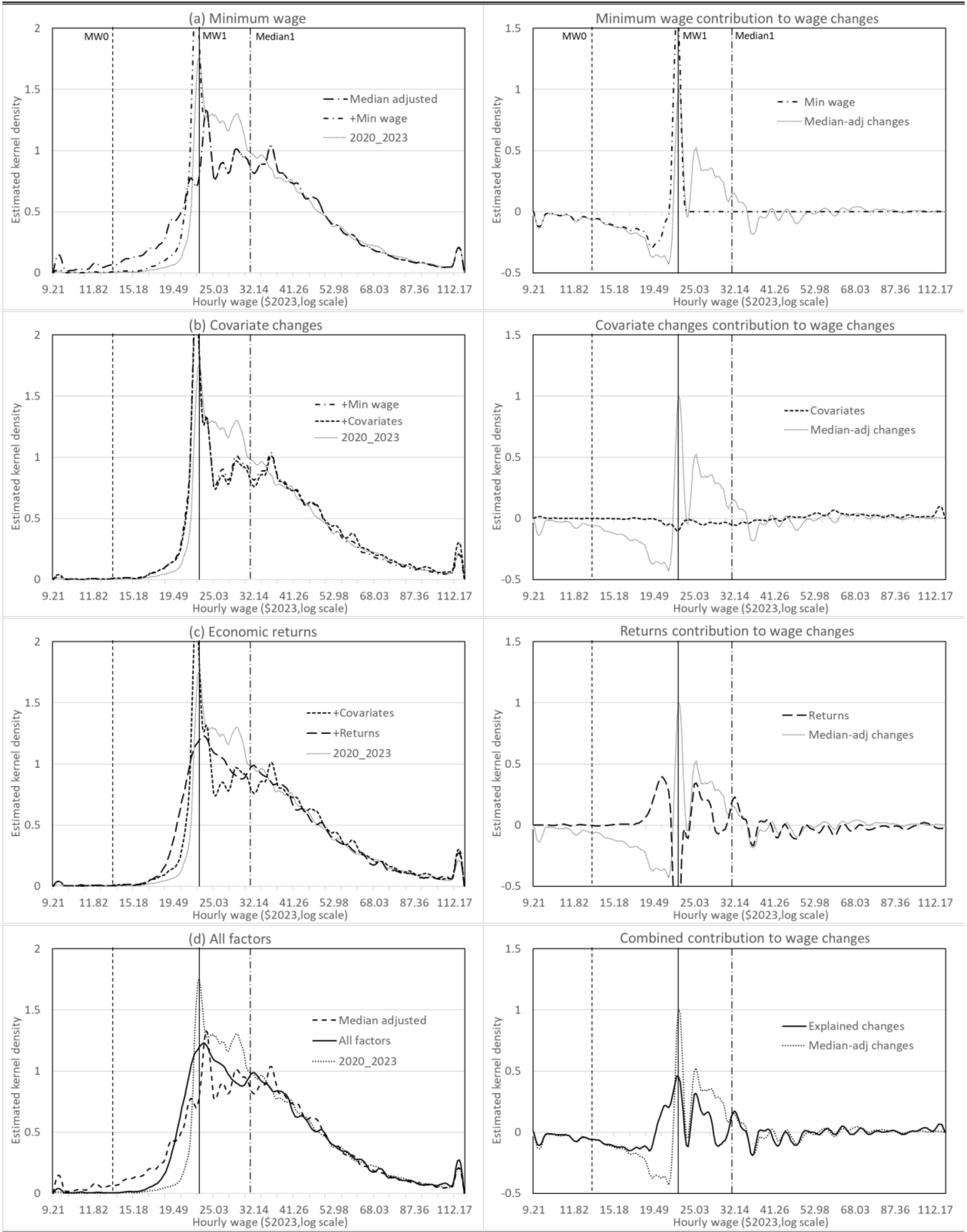
Notes: Estimates are based on distribution regressions with 46 cut-points (i.e. 47 intervals). The total number of observations used is 17,692,200, and R-squared=0.635. The regressions control for bin-effects, a quadratic in age, gender, ethnicity (Pakeha only, Māori only, Pakeha and Māori, Pacifica, and other), highest qualification (none, school, post-school, and university qualifications), and interactions between these demographic controls and the wage bin boundaries; and sub-period effects, and round dollar nominal wage values interacted with the sub-period indicators.

Figure A1: Wage and salary employment rate and weekly hours worked trends



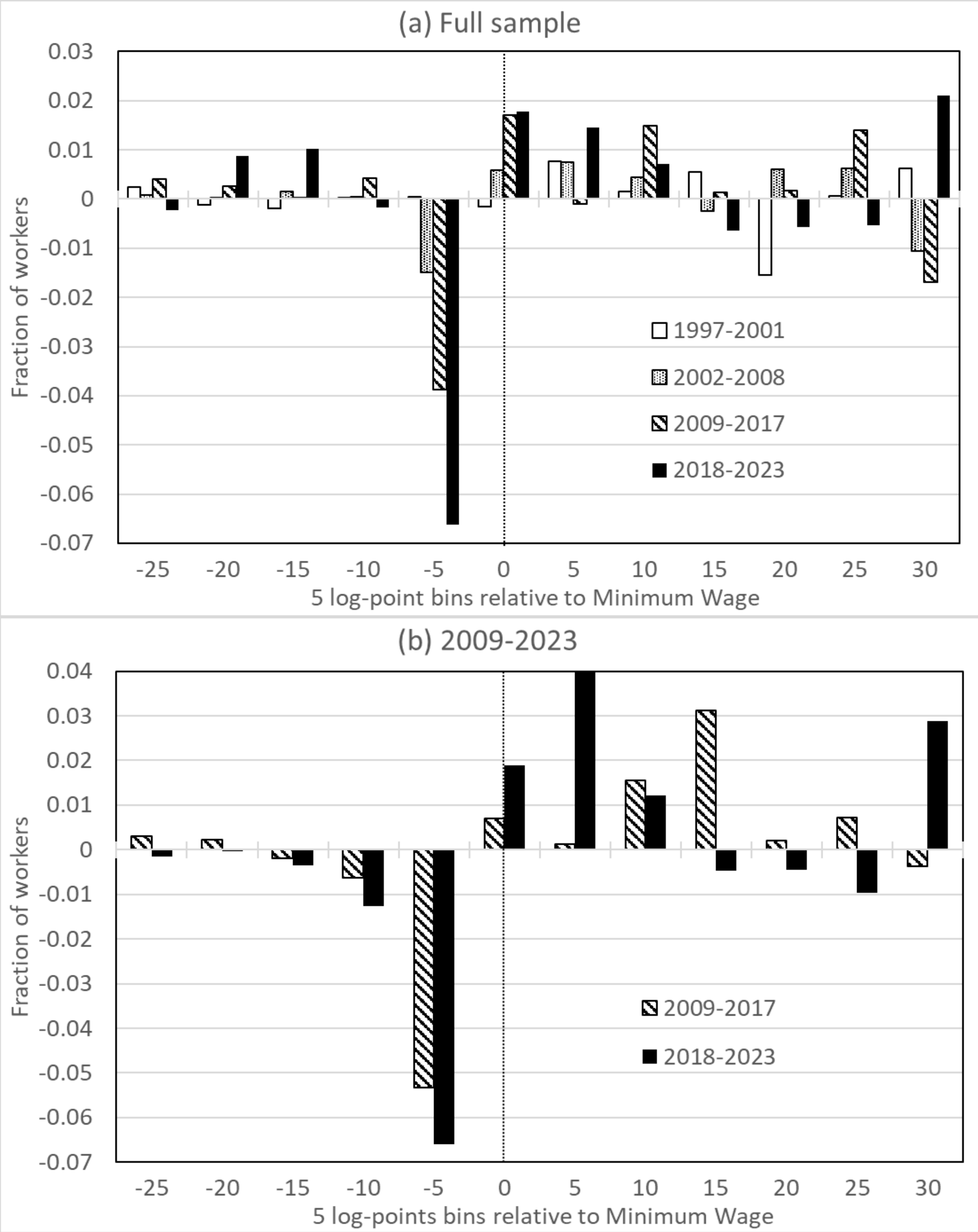
Notes: authors' estimates from HLFS data.

Figure A2: Alternative sequence based on relative rank replacement of lower tail wages



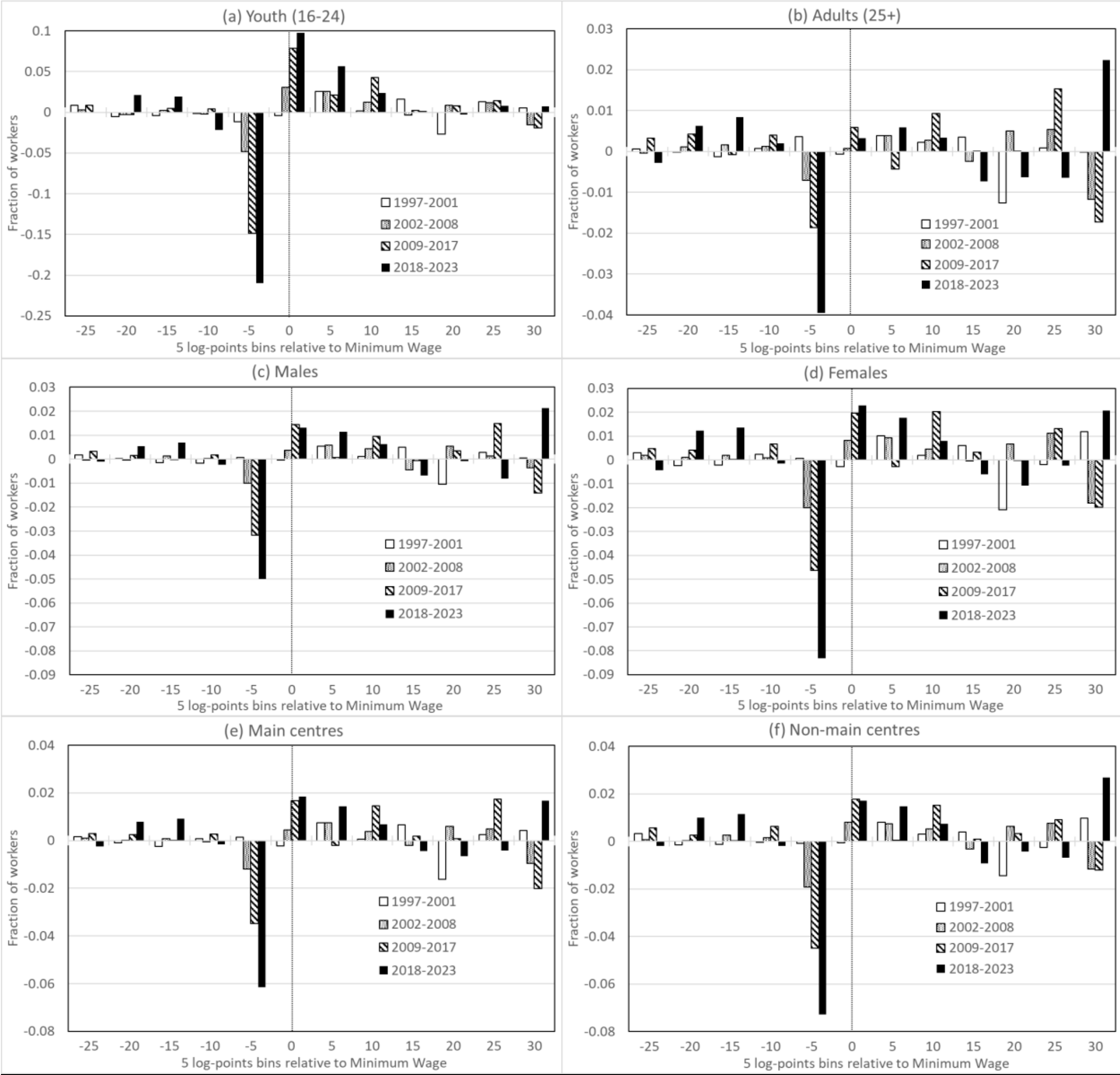
Notes: see notes to Figure 6.

Figure A3: Estimated minimum wage effects on wage distribution



Notes: The estimates in panel (a) are derived from coefficients in distribution regressions reported in Table A1. The estimates in panel (b) are derived from analogous regressions estimated over 2009-2023.

Figure A4: Estimated minimum wage effects by subgroups



Notes: The estimates are derived from coefficients distribution regressions for each subsample. The regressions control for wage bin-effects (relative to year-specific medians), a quadratic in age, gender, ethnicity (Pakeha only, Māori only, Pakeha and Māori, Pacifica, and other), highest qualification (none, school, post-school, and university qualifications), and interactions between these demographic controls and the relative wage bin boundaries; and sub-period fixed effects, and round dollar nominal wage values interacted with the sub-period indicators.