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WAGE GROWTH DISTRIBUTION AND CHANGES OVER TIME: 2001-2018

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NON-TECHNICAL SUMMARY

As in many other countries, employees in Australia have experienced declining wage growth since the 2008 Great Financial Crisis. The slowing wage growth has received much attention from policy makers and central banks, because of the social impact it could have by making households vulnerable to financial distress. The low wage growth has been surprising to economists given the low unemployment rate up to 2018, and various macro-oriented explanations have been given to explain the decline in wage growth. However, few studies examine how the decline in wage growth has affected different groups of employees – for example to what extent the slow-down in wage growth varies among employees with different demographic or job characteristics. We study how wage growth varies among Australian full-time employees over the 2001-2018 period, using the Household, Income and Labour Dynamics in Australia (HILDA) Survey. This paper has two sets of research questions and key results.

First, to what extent is wage growth explained by individual characteristics and job characteristics? We show that after increasing between 2002 and 2007, real (and nominal) wage growth has indeed slowed down from 2008 onwards. Similar results are found for part-time employees. We argue that the real wage growth may have been relatively high at around 5 per cent in 2007 instead of being relatively low at around 2 per cent in recent years. Moreover, our empirical analysis shows that wage growth seems to a large extent determined by employee characteristics such as age, education, employment contract, occupation and industry. Gender appears less important for wage growth.

Second, how does the role of employees' characteristics in wage growth change over the period 2001-2018, focussing on the Global Financial Crisis (GFC) and the recent slow-down in wage growth? Interestingly, we show that the employee's education is most important for wage growth in the pre-GFC period, whereas occupation is particularly relevant in the post-GFC period. This observation suggests decreasing returns to education and an increasing importance of specific occupations. Specifically, employees who have occupations that are more cognitive, less routine, such as managers and professionals, experienced relatively high wage growth from 2014 onwards. Moreover, we show that employees in insecure –casual– jobs receive a wage growth premium during the economic upturn and a penalty during the economic downturn. This finding indicates that the returns to casual jobs are pro-cyclical and strongly depend on labour demand driven by, for example, cyclical changes to specific economic sectors in the labour market.

The results suggest that wage growth inequality between employees is relatively independent of where the economy is in the business cycle, and that the differences between employees are more substantial than the year-to-year variation. Taken together, our findings are relevant for policy makers, as they inform which subgroups of employees are at risk of lower wage growth.

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ABSTRACT

This paper investigates how wage growth varies among Australian employees with different individual characteristics and job characteristics, and how the role of these characteristics has changed over the 2001-2018 period. The results show that after increasing between 2002 and 2007, wage growth had significantly slowed down post 2008, and particularly from 2013 onwards, returning to the levels of the early 2000s. Employees' age, education, employment contract, occupation and industry explain a large share of differences in wage growth between individuals, and these characteristics are more important than aggregate business cycle effects. Conversely, the employee's gender seems less important. Interestingly, the employee's occupation is more important post-2008 than pre-2008, with managers and professionals experiencing substantially higher wage growth than others since 2014, whereas education was more important pre-2008. Finally, we find that casual employees receive a wage growth premium during the economic upturn and a penalty during the economic downturn.

Keywords: individual wage growth; aggregate wage growth; business cycle; wage differentials

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1. Introduction

In recent years, a slow-down in nominal and real wage growth has been observed internationally in the US, Canada, Australia, UK and several European countries (Elsby et al., 2016; Pinheiro and Yang, 2017; Bell and Blanchflower, 2018a; Cassidy, 2019). The slowing wage growth has received much attention from policy makers and central banks, because of the social impact it could have by making households vulnerable to financial distress. The low wage growth has been surprising to economists given the low unemployment rate up to 2018 (Daly and Hobijn, 2016; Bell and Blanchflower, 2018a,b), and indeed actual wage growth has been lower than forecast wage growth in the US and Australia (Pinheiro and Yang, 2017; Cassidy, 2019). Various macro-oriented explanations have been given to explain the decline in wage growth.[1] However, few studies examine how the decline in wage growth has affected different groups of employees – for example to what extent the slow-down in wage growth varies among employees with different demographic or job characteristics.

We fill this gap by addressing two research questions around low wage growth in Australia, taking a micro-oriented perspective where wage growth is defined as the within-individual change in hourly wage from one year to the next. First, to what extent is wage growth explained by individual characteristics and job characteristics? Second, how does the role of employees' characteristics in wage growth change over the period 2001-2018, focussing on the Global Financial Crisis (GFC) and the recent slow-down in wage growth? Additional evidence on which employee characteristics explain differences in wage growth can inform more effective (wage) policy design by determining: who is affected, whether there is a need for concern regarding low wage growth, and which policy levers may be relevant. Most macro-economic studies have focussed on nominal wage growth, but since individual well-being is determined by real income, we use real and nominal wage growth in the analyses of this paper.

Differences in wage growth across subgroups of employees can be explained by human capital theory and/or by search and matching theory (Bowlus and Liu, 2013; Lagakos et al., 2018). The two theories are not mutually exclusive, and both are likely to be relevant to some extent. Based on human capital theory, we expect that the most able employees are provided with the best opportunities to accumulate human capital and, as a result, experience the highest wage growth over their careers. Consistent with this literature, we hypothesise that these subgroups are characterised by: (i) lower age, as the incentive to learn and to accumulate human capital reduces with age,

[1]Explanations include an increase in flexibility of wages in response to market conditions, decrease in unionisation rates, labour market slack, underemployment, changes in workforce composition, and weak labour productivity growth (Jacobs and Rush, 2015; Daly and Hobijn, 2016; Brouillette et al., 2017; Bell and Blanchflower, 2018b; Andrews et al., 2019).

and young employees are also the least experienced with the most still to learn; (ii) higher educational attainment, as the ability to learn increases with education; and (iii) long-term contracts as opportunities to learn are more likely to be provided by employers to employees on permanent contracts as employers expect these employees to be in their firm for a longer period of time, making investment in these employees more worthwhile.

Differences in wage growth patterns over time across subgroups can be explained by search and matching theory. Search and matching theory predicts that employees who are more able to move to better paid employment will realise higher wage growth (Burdett, 1978; Burdett et al., 2011). The literature indicates that subgroups of employees who are likely to do better in terms of job-to-job mobility and job matching are younger employees who face low mobility costs, and employees who have higher education as there is high demand for their skills (Manning, 2003). This leads to employees in high demand experiencing more wage growth through increased job-to-job mobility and bargaining power, especially during economic upturns in tight labour markets (Hirsch et al., 2018). In contrast, frictions in the labour market and misallocation have led to poor labour market outcomes for employees, especially for employees who face low labour market demand. Indeed, the demand side of the labour market has changed due to structural changes in specific economic sectors over the last decades (Gregory et al., 2019). For example, job polarisation caused by technological change and automation of jobs decreased demand for employees in occupations performing routine tasks relative to employees in occupations performing cognitive tasks. In routine jobs the scope for wage growth is thus likely to be more limited.[2]

To answer our research questions we use the Household, Income and Labour Dynamics in Australia (HILDA) Survey 2001-2018, following all respondents aged 21 to 64 in full-time employment. We focus on full-time employees to limit the confounding effect of transitions between part-time and full-time positions on wage growth. We use the within-individual year-to-year log change in nominal hourly wage in our descriptive analyses. We use the log nominal wage and the log real wage as the dependent variables in a fixed effects (FE) panel data analysis and in a first differences (FD) panel data analysis, while also controlling for changes in aggregate factors such as award rates and collective/enterprise agreements that outline minimum pay rates. Differences in wage growth over time by employees' characteristics are estimated by including interaction terms between calendar year dummies and characteristics. When using nominal wages, inflation is incorporated in the year effects.

[2]Differences in job preferences may also affect wage growth. That is, if someone is more selective with regard to the non-financial features of the job that they are willing to work in, then a standard job search model suggests that the wage offer curve is less steep due to a slower arrival rate of jobs. This may be more relevant for women than men (Loprest, 1992; Goldin, 2014). Additionally, negative (positive) discrimination may play a role in wage growth but this is outside the scope of this paper.

Our results show that post 2008, and particularly from 2013 onwards, nominal and real wage growth were significantly lower than just before 2008. Nominal wage growth has been stable in the last few years, while real wage growth has been more volatile in the post-2008 period (due to fluctuations in inflation), but there seems to be a downward trend returning to the real wage growth levels of the early 2000s. Similar results are found for part-time employees. Notably, results from different specifications in our paper consistently show that the employee's age, education, occupation and industry explain a large share of differences in wage growth (compared to year-to-year differences), whereas the employee's gender appears less important. Interestingly, the employee's occupation is more important post-2008 than pre-2008 with managers and professionals experiencing more substantial wage growth than others, whereas education is important across all years but slightly more important in the pre-2008 period. The employee's age, industry and type of contract are important for wage growth over the entire period, with casual employees receiving a premium during an economic upturn and a penalty during an economic downturn.

The next section describes the data and sample selections. Section 3 provides a descriptive analysis of wage growth over the period 2001 to 2018. The approach used in the multivariate analysis is outlined in Section 4. Results are reported in Section 5, before concluding in Section 6.

2. Data

The HILDA Survey is based on a sample of Australian households, representative of the Australian population of households in 2001. All individuals over 15 years of age living in these households are interviewed face to face at annual intervals. We use 18 waves over the period 2001-2018 of the HILDA Survey, following individual wage and salary workers aged 21 to 64 in the sample of analysis. We exclude individuals aged below 21 to avoid the effects of the youth minimum wage, and its yearly increase with age for those under 21.

2.1. Dependent Variables

To limit the impact of outliers on our results, we follow the literature in using the log hourly wage and the change in log hourly wage as the dependent variables in our multivariate analyses. We use the logarithm of nominal hourly wage as the dependent variable in our FE empirical analysis. The hourly wage is constructed by taking the usual weekly earnings divided by the usual weekly hours worked. We also construct a within-individual year-to-year change in nominal hourly wage for our descriptive analysis and FD empirical analysis. The respondent needs to be observed in at least two consecutive waves to compute this wage growth variable.

Real hourly wage is computed by deflating the nominal hourly wage using the Consumer Price Index (CPI) of that year. Using the CPI baseline year used by the Australian Bureau of Statistics, real hourly wage is expressed in 2012 dollars. The real hourly wage is used in our FE empirical analysis. Real wage growth is computed from the within-individual year-to-year change in real hourly wage, and is used in the FD empirical analysis.

We compare the nominal wage growth variable to the measures based on macro-level industry-specific data such as the Wage Price Index (WPI), Average Weekly Ordinary-Time Earnings (AWOTE) and Average Annualised Wage Increase (AAWI).[3] We include all three indexes as each of them measures a related but different aspect of labour costs. The WPI is based on a sample of jobs and captures changes in wage rates excluding bonuses, while controlling for changes in the composition of the workforce. The AWOTE is based on a sample of employees and captures changes in total earnings by individuals, which includes bonuses and depends on changes in the workforce. The AAWI is based on a sample of employees covered by enterprise agreements and captures changes based on federal enterprise wage agreements in all economic sectors. Hence, the compositional changes due to new entries (of inexperienced employees) and exits (of experienced employees) are absorbed in the aggregate wage indexes. These three indexes are used to summarise the aggregate changes in earnings for the Australian population. This allows us to compare the individual wage growth experienced by full-time employees to these aggregate measures over the last two decades.

2.2. *Covariates and Sample Selections*

Our analyses include a rich set of variables with information on individuals and the households in which they live, including gender, age, education attained, current education/training enrolment, number of household members, number and age of children, Indigenous status, country of birth, marital status, individual's annual personal income (categorised in year-specific quintiles), long-term health condition and location of residency at the SA3 level; as well as information on job characteristics such as type of contract (permanent/fixed-term/casual), occupation, industry and type of job (public/private). Job-to-job turnover is represented by an indicator variable that equals one if the tenure in the job is less than one year and zero otherwise. A transition in occupation is represented by an indicator variable that equals one if the current occupation differs from the occupation in the previous year. A transition in industry is represented by an indicator variable that equals one if current industry differs from industry in the previous year.

[3]The following data on these macro-economic measures are used. For the WPI, we use the industry-specific ordinary hourly rates of pay excluding bonuses in June of each year (Australian Bureau of Statistics, 2018b). For the AWOTE, we calculate industry-specific year-to-year changes by using the gross average weekly ordinary time earnings for full-time employees in May of each year (Australian Bureau of Statistics, 2018a). For the AAWI, we use the industry-specific trends historical table in June of each year (Australian Government Department of Jobs and Small Business, 2018). WPI and AWOTE numbers are not available for the Agriculture, Forestry and Fishing industry. For inflation, we use CPI data from June of each year.

Our sample of analysis is determined by the following sample selections. We only keep individual-year observations of the main job of full-time employed individuals, i.e. individuals working more than 35 hours in their main job. This is an important selection as it eliminates the confounding effects of endogenous transitions from part-time to full-time work on wage growth. Specifically, wage growth varies considerably over the business cycle due to different transition rates between unemployment, part-time employment and full-time employment at different points in the business cycle.[4] By restricting our analysis to full-time employees, we focus on the within-group wage growth of full-time employees while taking out between-group composition effects. In a robustness check provided in Figure B6 of Appendix B, we show that our results also hold for a combined sample of full-time and part-time employees.

We further restrict the sample by excluding several employee-year observations that are more likely to be outliers. Employee-year observations involving employees working more than 80 hours in their main job are excluded. Employee-year observations involving employees earning more than A$10,000 a week or less than A$200 in their main job in nominal terms are excluded. We also remove the bottom 1 percentile and top 1 percentile (on an annual basis) of hourly wage and percentage growth in hourly wage. These selections limit the incidence and problems associated with outliers, and the volatility of wages and working hours, while not excluding too many observations.

3. Descriptive Analysis

For our analyses we use information from the pooled years 2001/02 to 2018.[5] Applying the sample selections described in the previous section, we have observations for 11,714 and 11,099 unique persons who are observed in full-time employment in at least two waves and at least two consecutive waves, respectively.

Figure 1 shows that average wage growth over the 2002-2018 period varied substantially (between around 6 to 11 per cent), and both mean and median wage growth are at their lowest levels in 2013-2015 and 2017. The patterns of wage growth reflect the patterns observed for the aggregate wage indexes, but the wage growth based on our sample is at a higher level in each of the observed years. These descriptive findings are consistent with reports by the Reserve Bank of Australia (RBA) on declining wage growth in Australia (Jacobs and Rush, 2015; Cassidy, 2019),

[4]For example, see Haefke et al. (2013); Daly and Hobijn (2017); Moscarini and Postel-Vinay (2018); Hyslop and Rice (2019).

[5]For several variables, e.g. change in hourly wage, we focus on the change from $t-1$ to t. Hence, in all graphs and tables related to these variables, including the FD analysis, data are included over the period 2002 to 2018. We exclude $t = 2001$, as we need information from the previous year to construct these variables.

and it is important to note that even full-time employees, who are among the least disadvantaged individuals in the population, have experienced lower wage growth in recent years.

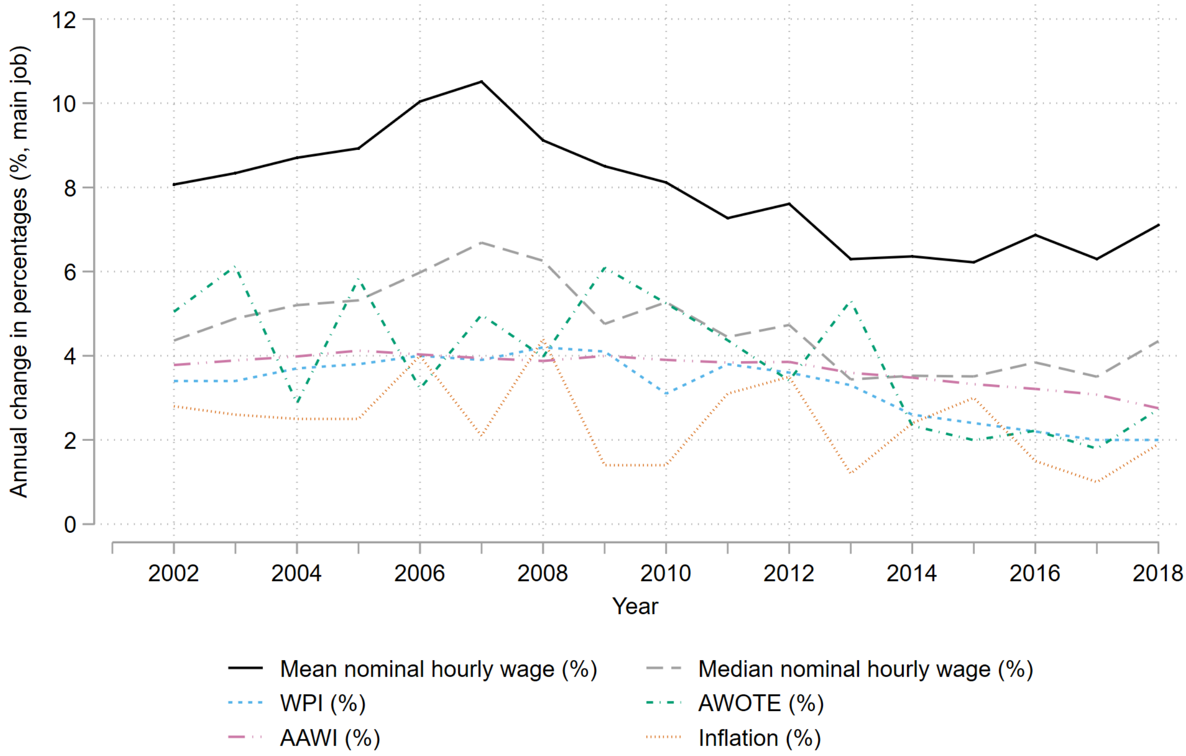


Fig. 1. Mean and median year-to-year changes in hourly wages, and the wage indexes (N=61,507). *Notes:* Full-time employees' mean and median changes in hourly wages are based on the individual HILDA Survey micro data. The WPI, AWOTE and AAWI indexes based on aggregate annual data in nominal terms.

We present summary statistics for our key variables in Table 1. Table 1 presents the range of values that nominal wages of employees take. The high individual-level wage growth is at least partly due to many employees receiving regular annual increases as a result of the presence of annual increments within a pay scale. These annual increments are often set within award rates, which are generally higher than the national minimum wage and depend on the industry, occupation and location of an employee. The award wages cause, from an international perspective, the relatively high minimum wages and high wage growth in Australia. For full-time employees in the HILDA Survey sample, the mean nominal hourly wage and median nominal hourly wage increased from about 20 and 18 Australian dollars in 2001 to about 38 and 34 Australian dollars in 2018, respectively. The aggregate wage indexes are based on industry-specific changes in wages using data on the entire population of Australian employees. We pay attention to differently defined macro-level wage growth by comparing the WPI, AWOTE, and AAWI with the average

Table 1
Individuals' summary statistics[a].

	N	Mean	Median	Min.	Max.
Nominal hourly wage (A$)	80,625	29.73	26.32	5.367	111.1
Growth nominal hourly wage (%)	61,507	7.683	4.555	-57.78	166.7
Nominal wage main job (A$, weekly)	80,625	1,294	1,123	200	7,135
Growth nominal wage main job (%)	61,507	7.566	4.256	-72.00	298.2
Working hours main job (weekly hours)	80,625	43.47	40.00	35.00	80.00
WPI (%)[b]	79,336	3.238	3.300	1.000	6.000
AWOTE (%)[b]	79,336	3.829	3.771	-5.912	12.34
AAWI (%)[b]	80,625	3.690	3.719	2.011	5.127
Inflation (%)	80,625	2.559	2.500	1.000	6.100
Growth nominal hourly wage (%, annual level)[c]	17	3.727	3.977	1.699	5.498

Notes: a) The time period under observation is from 2001 to 2018. The number of individuals equals 11,714 for the level variables and 11,099 for the growth variables; these are different since individuals need be observed for at least two consecutive years to construct the growth variables. The number of observations, sample mean, median, minimum and maximum are provided.
b) Employees' WPI, AWOTE and AAWI indexes are in nominal terms and are based on annual statistics by industry, linked to individuals in our HILDA Survey sample by industry and year. The number of observations for WPI and AWOTE is lower as there is no information available for the economic sector "Agriculture, forestry and fishing".
c) Computed by taking the annual change in the average hourly wage of all employees. The full sample is used, including all employees in a full-time or part-time job and employees churning in and out of employment ($N = 111,246$), to make it more comparable to the aggregate wage indexes.

individual wage growth observed in our sample of full-time employees in the HILDA Survey data. We link inflation, WPI, AWOTE and AAWI to individuals in the HILDA Survey sample on the basis of year of observation and industry of the individual.

It is clear from Table 1 that average hourly individual wage growth observed in our sample is much higher than any of the aggregate wage indexes indicate. The difference between the hourly wage growth and the wage indexes can be explained by our focus on full-time employees as well as by other sample selections. For example, individuals who churn in and out of employment are less likely to be included in our analysis, since the individuals in our sample of analysis need to be in full-time employment for at least two consecutive waves to be included. Moreover, employees who churn in and out of employment are more likely to be affected by structural changes in labour demand such as automation (Gregory et al., 2019). More generally, disadvantaged individuals are less likely to be represented in our analysis (especially post-GFC), as they are more likely to be displaced and remain non-employed, or only gain part-time employment.[6] Indeed, the last

[6] See Tables A1 and A2 for descriptives on the average nominal wage growth by subgroup for the 2002-2008 versus the 2009-2018 period (roughly pre- and post-GFC).

row of Table 1 shows that the annual-level wage growth of 3.7 per cent across all employees in the HILDA Survey is comparable to that reported through the aggregate wage indexes. This average wage growth is computed by taking the annual change in the mean of hourly wages of all employees, including full-time and part-time employees churning in and out of employment.

Examining the distribution of the change in log nominal wage, Figure 2 displays a distribution ranging from negative to positive values, which is slightly skewed towards positive values. This distribution is plotted for four different years and shows that 2007 is the most different, with a clear shift to the right, indicating more higher positive wage changes. Since 2007, both the size and frequency of wage increases have reduced. The years 2012 and 2017 have slightly shifted to the left (indicating lower wage growth) compared to 2002 (and 2007).

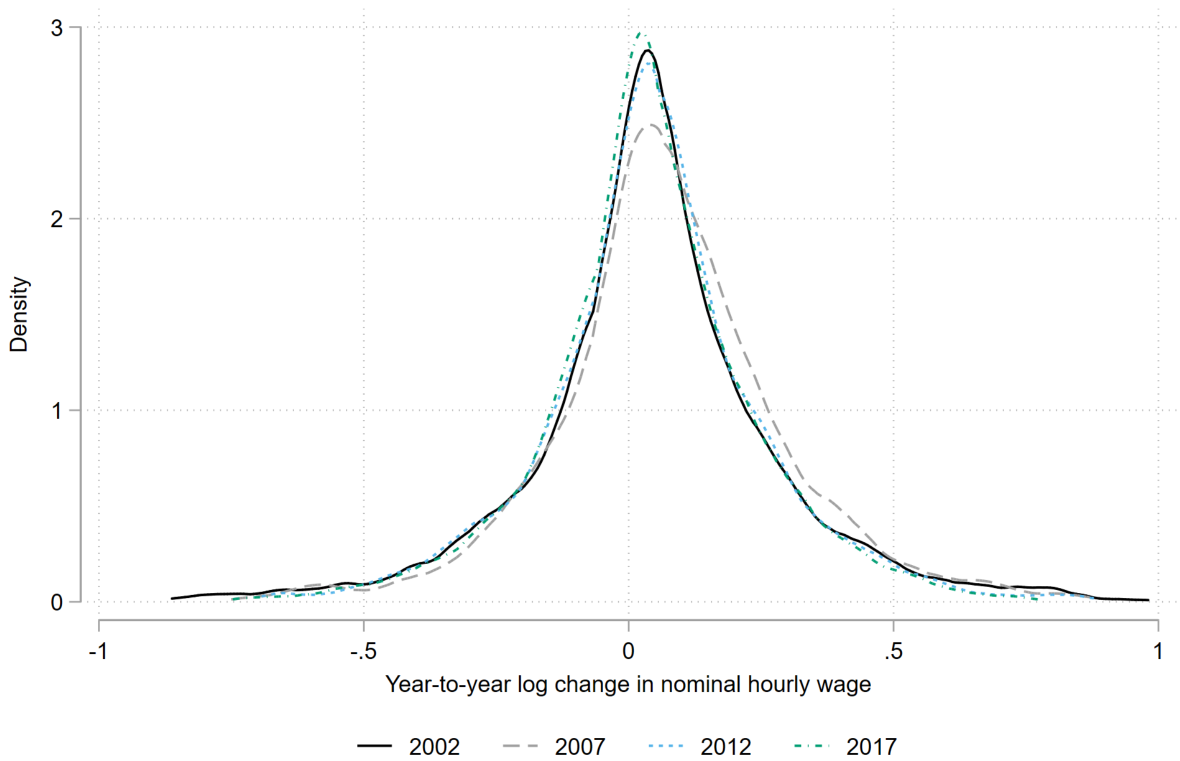


Fig. 2. Year-specific density plot of log change in nominal hourly wages (N=61,507).
Note: Full-time employees' log changes in nominal hourly wages are calculated using HILDA Survey micro data.

Figure 2 is consistent with several findings in the literature. First, there is some evidence of a nominal wage stickiness (visible in the large peak at zero change) and a resistance to nominal wage cuts (visible from the relatively low share of employees who experience negative year-to-year wage changes).[7] However, consistent with Elsby et al. (2016) and Elsby and Solon (2019),

[7]This is also observed in Figure B1 of Appendix B, which shows a graph of the year-specific density plots of

the still substantial fraction of individuals experiencing a decline in hourly wages as observed in Figure 2 highlights that nominal wage stickiness is less binding than is generally assumed. Second, wage increases are pro-cyclical, as evidenced by the higher share of positive year-to-year log changes in 2007. This finding can be explained by higher job-to-job mobility and increased bargaining power during economic upturns (Hirsch et al., 2018).

4. Methodology – Empirical Models

Our two research questions are addressed by multivariate panel analyses in which we explore employee characteristics that explain differences in wage growth patterns over time, while including a large set of covariates and controlling for area level and macro-economic factors. We first estimate a fixed-effects wage level model using all available waves of data.

We specify the following empirical model to estimate the effect of various individual characteristics and job characteristics on log hourly wage:

$$log(w_{irt}) = \beta' X_{irt} + \alpha_i + A_r + D_t + \varepsilon_{irt} \tag{1}$$

$$i \in 1, 2, ..., N;\ r \in 1, 2, ..., R;\ t \in 2001, 2002, ..., 2018$$

where subscripts i, r and t denote the employee, regional residence SA3 and year, respectively. The employee's characteristics, including demographics, occupation and industry, are represented by X_{irt}. β represents the parameter estimates on the employees' observables, which allow us to determine the main individual and job characteristics that influence wage levels.[8] Individual-specific fixed effects are denoted by α_i, which are included to control for time-constant unobserved heterogeneity such as the employee's motivation and ability. The fixed effects specification allows us to focus on the impact of local macro-economic circumstances and individual characteristics that change over time. A_r refers to residential area fixed effects that control for local labour market conditions at the SA3 regional level. We include calendar year fixed effects, D_t, to estimate the year-to-year overall change in wages including business cycle effects and inflation. ε_{irt} refers to the idiosyncratic error term.

We estimate (1) using nominal hourly wages. We also estimate (1) based on real hourly wages deflated by CPI, to control directly for changes in inflation over time. This results in the same estimated coefficients, except for the calendar year fixed effects, D_t, which no longer include

percentage changes in nominal hourly wages.

[8]When sufficiently small, β can be interpreted as the approximate percentage increase in wage as a result of a one-unit increase in X_{irt}. The precise percentage change is $exp(\beta) - 1$.

inflation. Year-to-year wage change (holding individual employee characteristics constant) can be computed using $D_t - D_{t-1}$.

Equation (1) does not allow for different wage growth patterns over time for employees with different characteristics. Equation (2) extends the model specified in equation (1) by estimating separate parameters on X_{irt} for each calendar year:

$$log(w_{irt}) = \beta' X_{irt} + \alpha_i + A_r + D_t + \eta_t' X_{irt} + \varepsilon_{irt} \tag{2}$$

The additional parameter of interest is denoted by η_t, which represents the difference in wage growth between specific groups of interest versus the reference groups (e.g. women versus men) in year t relative to reference year 2001. Annual wage growth of a specific group relative to a reference group in year t is then $\eta_t - \eta_{t-1}$.[9]

When estimating wage levels (as specified in equation (1)), and using the estimated coefficients to compute wage growth, impacts from compositional changes of the sample are included in our wage growth numbers as individuals do not need to have consecutive year observations to be included in the estimation. As a result the individuals (and thus the characteristics of the sample of analysis) on which the year effects are based may vary (slightly) from year to year. In our analysis we also re-estimate equation (1) in an FD specification, which only includes observations with at least two consecutive observation years (i.e. the continuing employees).[10]

$$log(w_{irt}) - log(w_{ir',t-1}) = \beta'(X_{irt} - X_{ir',t-1}) + A_r - A_{r'} + D_t - D_{t-1} + \varepsilon_{irt} - \varepsilon_{ir',t-1} \tag{3}$$

$$i \in 1, 2, ..., N;\ r, r' \in 1, 2, ..., R;\ t \in 2002, 2003, ..., 2018$$

We compare the results based on equations (1) and (3) to assess whether a more restricted sample of analysis affects the estimated coefficients, in particular the calendar year fixed effects.

5. Empirical Analysis

5.1. Wage Growth Differences Among Employees

We estimate a basic FE wage level model (as specified in equation (1)), which controls for a broad range of individual and job characteristics, in turn using nominal and real wages. The

[9] The differences in average wage level between specific groups of interest versus the reference groups in year t are measured by $\beta + \eta_t$.

[10] The restriction of only using consecutive observation years leads to a sample of more advantaged employees with more stable employment. The statistics reported in Table A1 are consistent with this observation, as these illustrate that by selecting consecutive observation years, individuals from the lowest income quintile are excluded from the sample disproportionally.

implied year-to-year wage growth is graphically presented in Figure 3.[11] With all controls (and individual- and region-specific effects) included, the pattern of relative wage growth is still similar to that in Figure 1, but at a lower level. Specifically, Figure 3 shows that nominal wage growth declined by 3.5 percentage points from 7 per cent in 2007 to 3.5 per cent from 2013 onwards. As expected, the real wage growth is always lower than nominal wage growth, with less than 1 per cent real wage growth on average in 2013 and 2014.

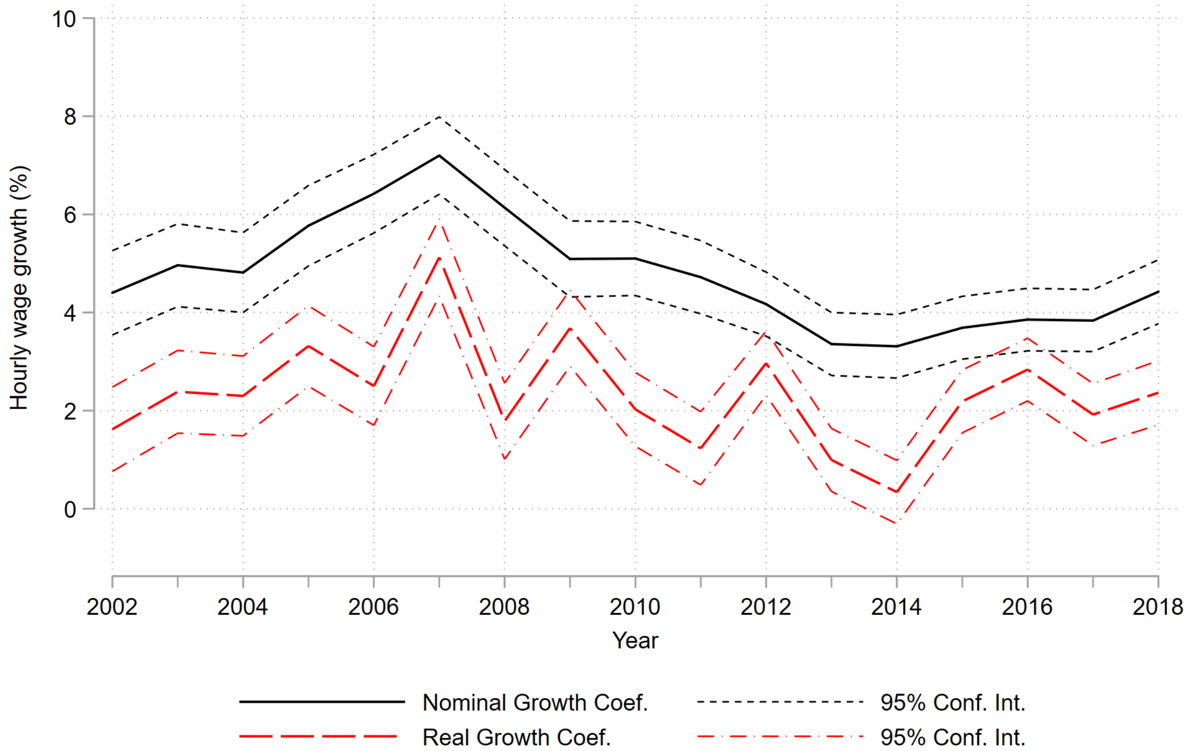


Fig. 3. Year-to-year wage growth (Equation (1)).
Notes: The nominal and real wage coefficients are based on two sets of FE regressions (see column 5 in Table A3 for the set based on nominal wages; the results for real wages are available from the authors). The 95% confidence intervals are computed using clustered standard errors by individual. The regressions include zero-one indicator variables for age (8), education (4), number of household members (3), marital status (5), number of own resident children (3), type of contract (2), job occupation (7), job industry (18), private sector (1) and the SA3 regional location of the household (323). The sample of analysis includes 80,625 individual-year observations and 11,714 unique individuals. R^2 equals 0.52 and 0.23 for the nominal and real wage model, respectively.

Compared to 2007, the lower nominal wage growth from 2012 onwards has been striking.

[11] The estimated models contain a large number of coefficients by calendar year, which are presented most clearly through graphs. More detailed results are reported in Table A3 in Appendix A, while tables with full results including all estimated coefficients are available from the authors upon request. Cumulative relative wage growth is presented in Figure B3 in Appendix B.

However, it is around the same level as it was in 2002. Real wage growth is fluctuating much more, and although it is at an higher level in 2007 than in any other year, it is not clear that post-GFC real wage growth is consistently lower than in the early 2000s. This suggests that real (and nominal) wage growth may have been relatively high in 2007 instead of being relatively low in recent years.

We examine which employee characteristics explain differences in wage growth patterns over time. Specifically, we estimate an extended FE nominal wage level model (as specified in equation (2)), controlling for the same broad range of individual and job characteristics as before, with all these characteristics, except for the SA3 location, interacted with year of observation so that separate coefficients by calendar year can be estimated.[12] Figures 4 to 6 show relative year-to-year wage growth (graphs on the left-hand side) for a number of subgroups relative to a reference group. The graphs on the right-hand side in Figures 4 to 6 display the corresponding cumulative wage growth effects over the period 2002 to 2018, illustrating the long-term changes in wage growth over time. Figures 4 to 6 are all based on the parameter estimates from one single regression. For characteristics with many categories such as age and industry, we have made a selection of the categories to be included to limit the number of lines per graph. For the same reason of clarity, we have also excluded confidence bounds from the graphs, except in Figure 4a.

Figure 4a shows that differences in year-to-year wage growth by gender are never significantly different from zero in our period of observation. Conversely, in terms of cumulative wage growth since 2002, women fare more poorly than men which is just significant towards the end of the period (from 2012 onwards). As such, although our descriptive results suggest that women fare better than men in the post-GFC period (see Table A1), including observables such as education and occupation shows that the impact of gender on wage growth works through other characteristics.

The variations in wage growth by age are large and very clear: higher wage growth is observed for younger employees compared to older employees (see Figure 4b). However, Figure 4b does not allow for the fact that as employees become older, they would move from one age category to the next. As a result, the differences between age cohorts (50 percentage points over 17 years) are exaggerated. Differences in wage growth by birth cohort allow a more accurate wage growth path representation over the life cycle. See Figure B4 of Appendix B for the graphs of wage growth by birth cohort. Although better (at 40 percentage points), differences between birth cohorts are also exaggerated as employees are not observed over their entire life (or even career). Our findings

[12]Note that using real wages instead of nominal wages does not change the results of this specification, as inflation is captured by the main year effects and we are interested in the interaction effects between year and various characteristics.

are consistent with human capital mechanisms and with search and matching mechanisms, as discussed by Lagakos et al. (2018).

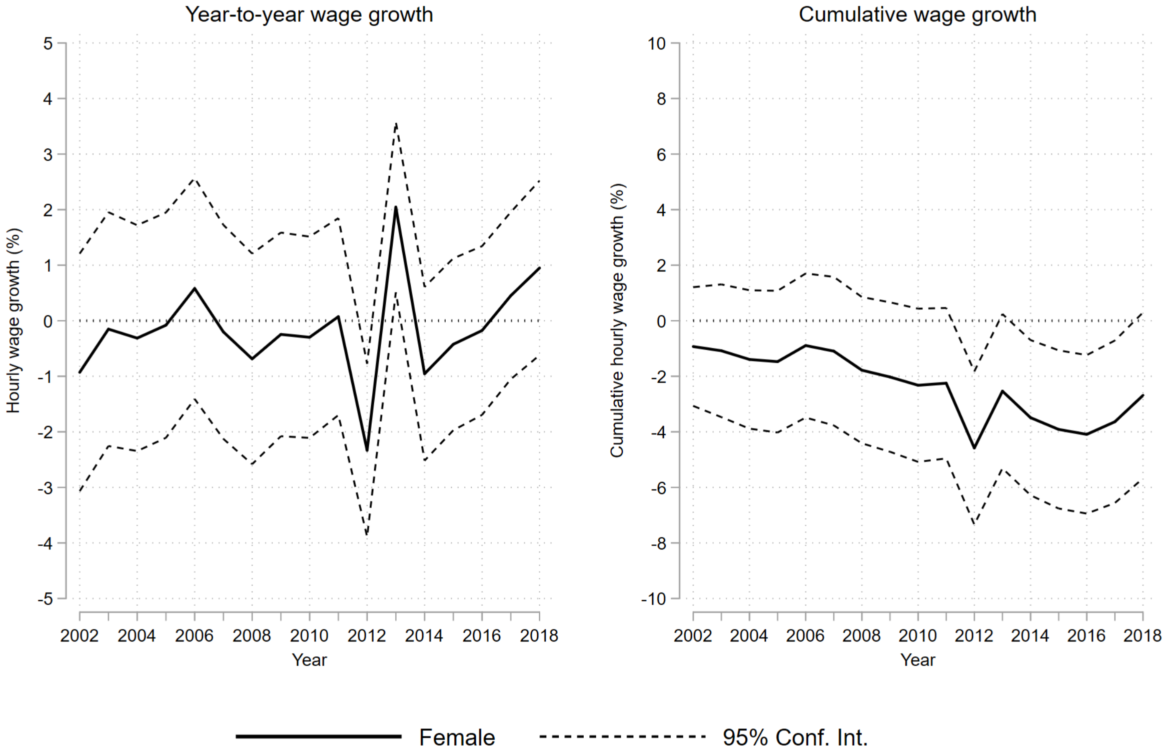
Education appears relevant for wage growth (Figure 5a), especially educational attainment at the university degree level provides additional wage growth in the pre-GFC period. Figure 5a shows clearly that the positive relationship of education with wage growth was much reduced post GFC, as is visible through the flatter/decreasing lines relative to the base category in the right-hand-side graph. This observation suggests decreasing returns to education in terms of wage growth, caused by job search and matching mechanisms, not by human capital mechanisms.

Employees in casual work (Figure 5b) have seen different variations in wage growth over time compared to other employees: pre-GFC employees on a casual contract received a wage growth premium, whereas post-GFC casual employees received a wage growth penalty.[13] The wage growth of employees with a fixed contract has been similar to employees on a permanent contract, maintaining a more or less constant wage growth advantage of around 4 per cent achieved in the first year. This is inconsistent with human capital theory that would predict larger wage growth for permanent employees, as investments in these employees are likely to be more worthwhile given that they are more likely to stay with the firm for a longer time. Conversely, the pro-cyclical wage growth premium and penalty for casual employees appears to depend on the business cycle, consistent with search and matching mechanisms.

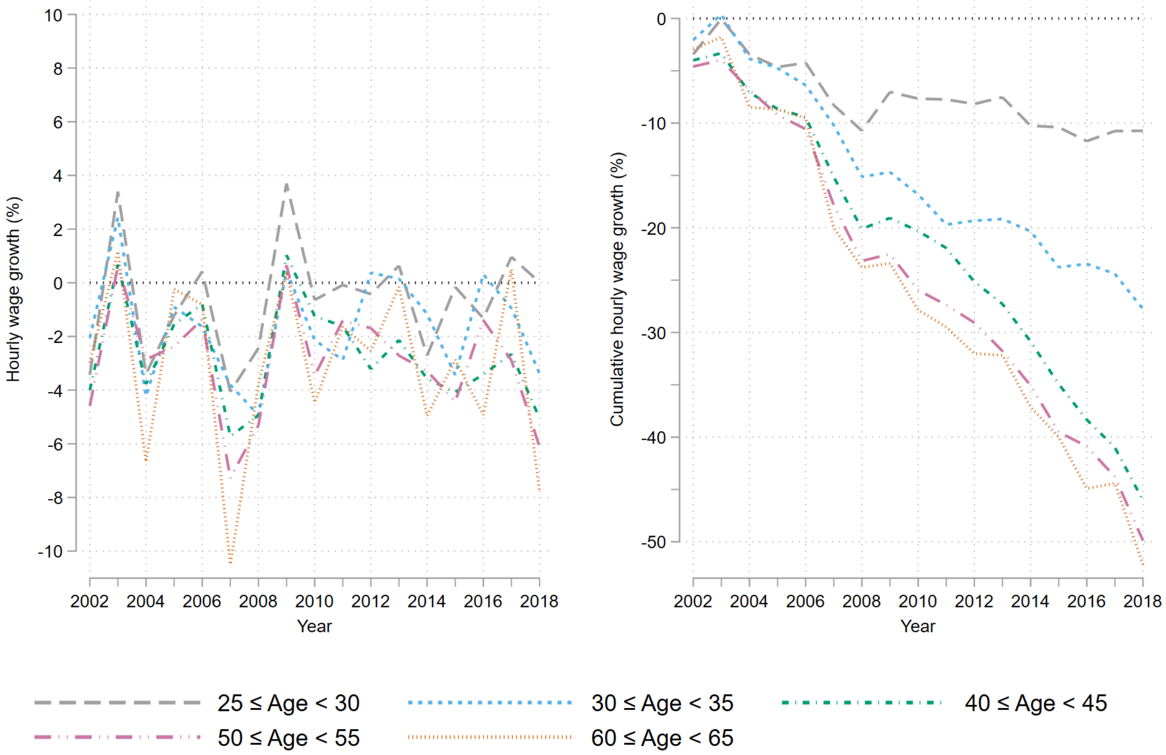
The results for the occupation indicators in Figure 6a show that employees who have more cognitive, less routine, occupations have a tendency to experience higher wage growth (although not necessarily significantly higher). These occupations include managers and professionals, who experienced steady wage growth in the post-GFC period, which was larger than that of other employees.[14] In contrast, occupations with more routine tasks such as machinery operators and labourers experience the lowest cumulative wage growth, which has become more evident in recent years. These findings are consistent with those reported by Fonseca et al. (2018), who focus on the importance of job polarisation for employment and wages in Portugal over the period 1986 to 2007. Our findings show that the role of occupation in wage growth becomes more pronounced in the post-2008 period, especially from 2011 onwards, as is clearly visible from the larger variation across occupations in cumulative wage growth in the right-hand-side graph of Figure 6a. This observation suggests that especially managers and professionals, able to exploit high labour demand, experience higher wage growth than other occupations.

[13] In Australia, casual employees are entitled to a premium on the hourly pay rate. This casual wage premium compensates for the lack of paid leave and job protection.

[14] See Autor and Dorn (2013) and Goos et al. (2014) for how a classification of occupations based on the Routine Task Intensity index is constructed for the US and Europe, respectively.

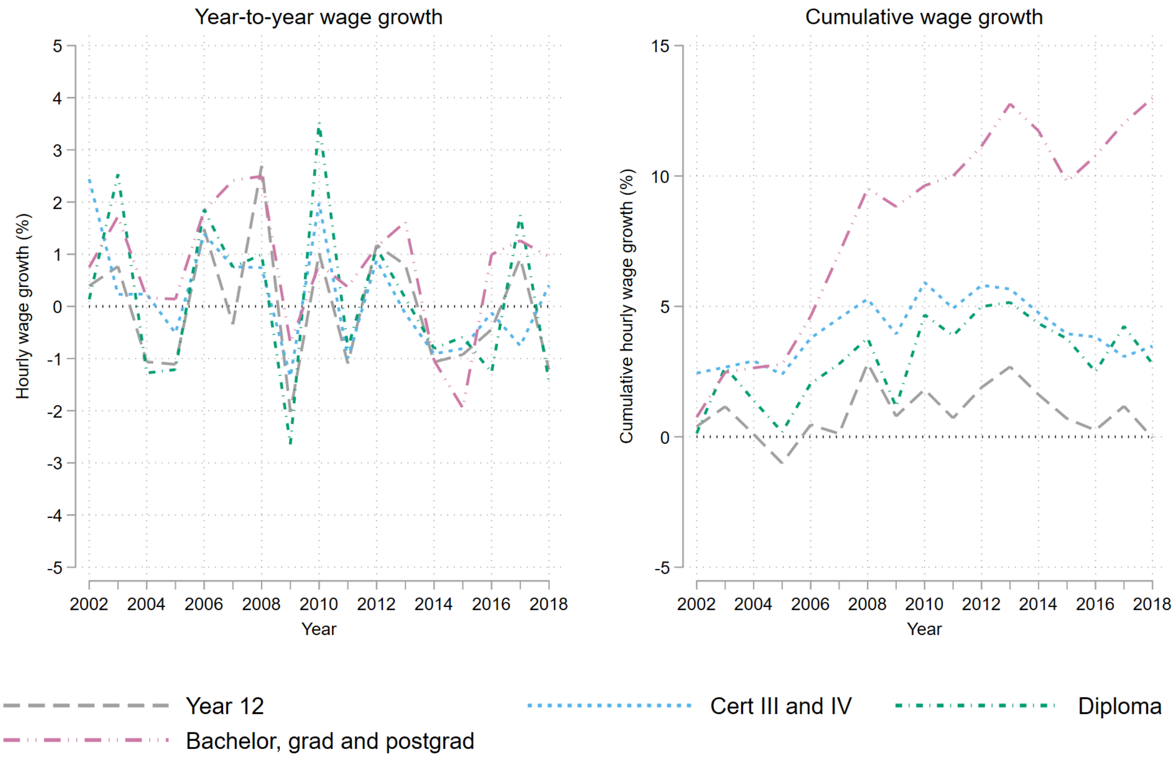


(a) Gender (relative to males)

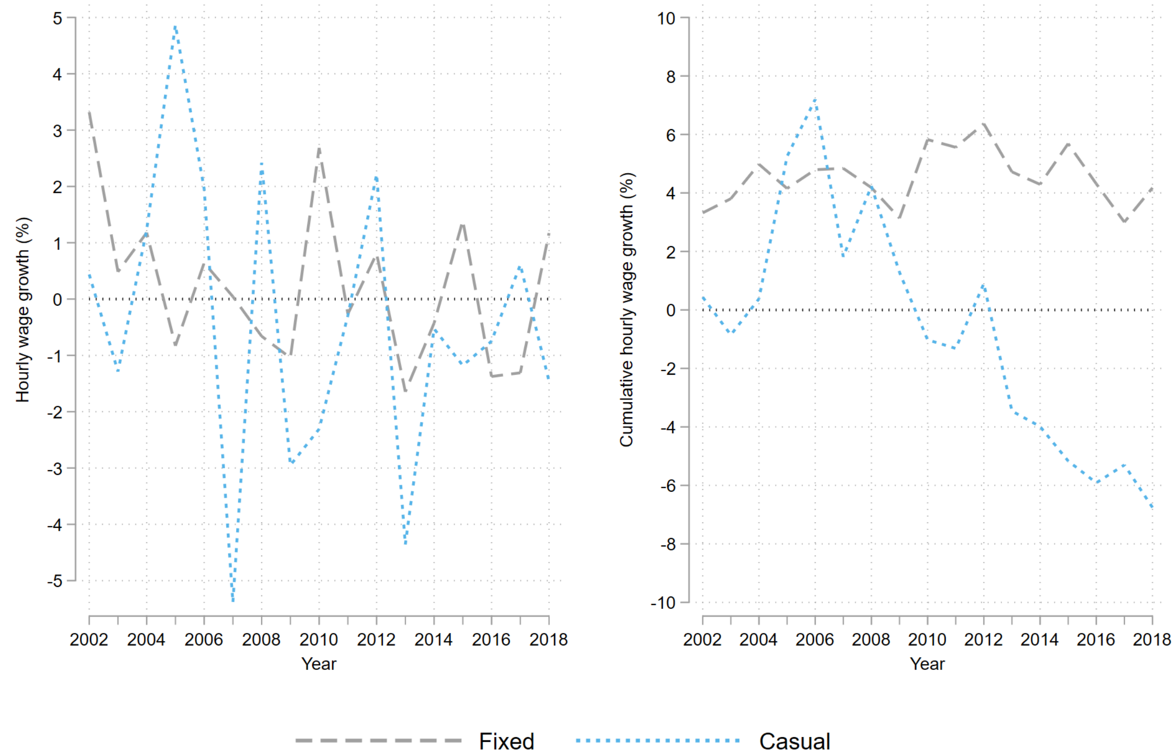


(b) Age (relative to age category 21 to 25)

Fig. 4. Year-to-year and cumulative relative wage growth by individual characteristics (Equation (2)).
Notes: All graphs in Figures 4-6 are based on the relevant $\beta + \eta_t$ from the same FE regression. The reference categories of gender, age and year consist of male employees, employees aged 21 to 25 years and year 2001, respectively. Except for the SA3 location, all individual and job characteristics are interacted with calendar year of observation, including the time-constant variables gender, Indigenous and born abroad. Several age categories are left out from Figure 4b to ensure clear graphs. R^2 of the regression equals 0.53. See Figure 3 for additional notes.

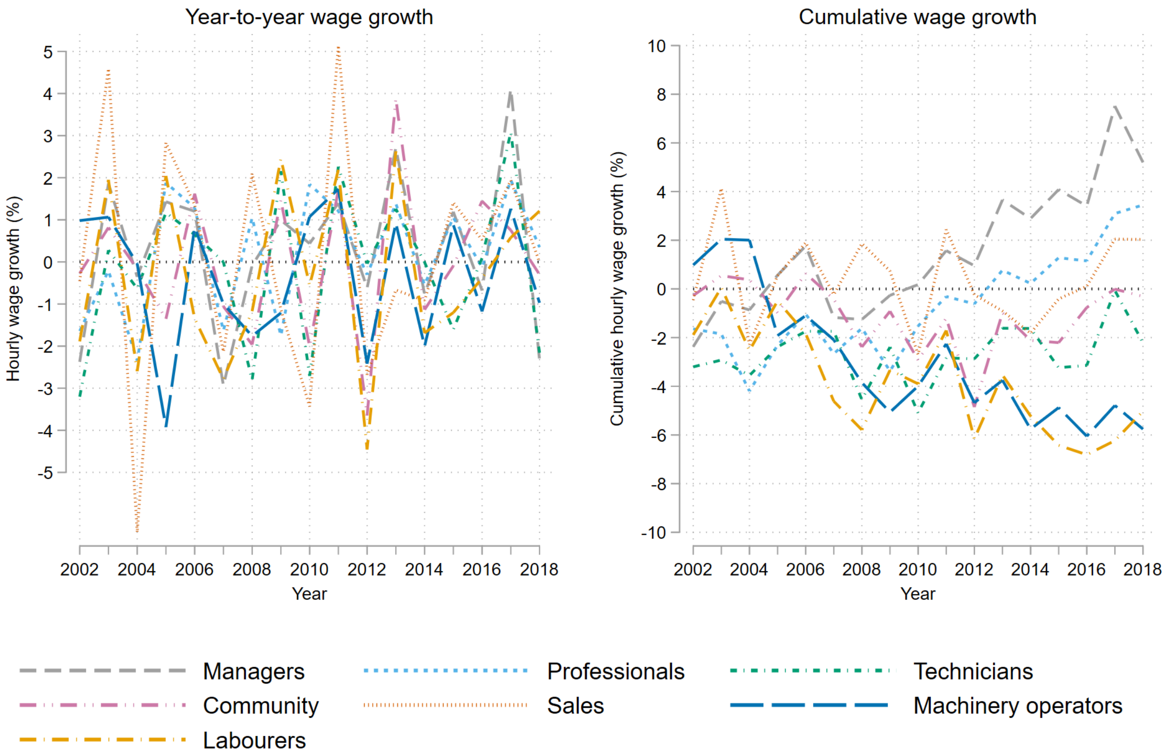


(a) Education (relative to Year 11)

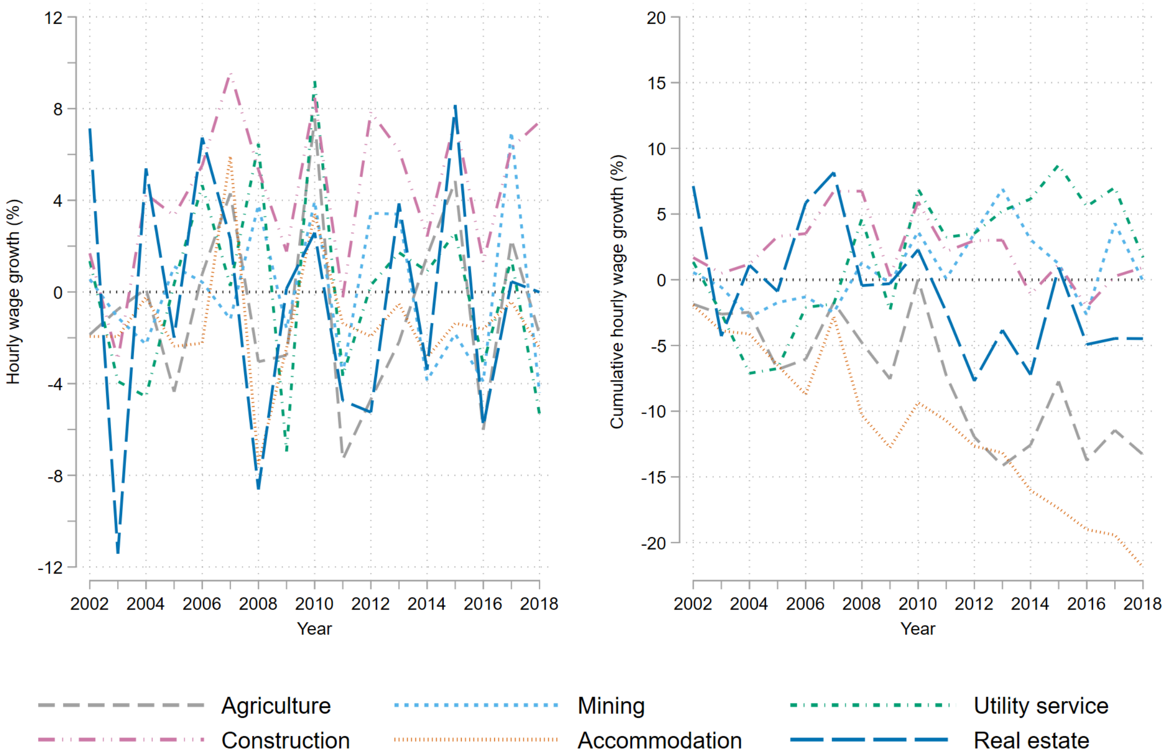


(b) Contract (relative to a permanent contract)

Fig. 5. Year-to-year and cumulative relative wage growth by individual characteristics (Equation (2)).
Notes: All graphs in Figures 4-6 are based on the relevant $\beta + \eta_t$ from the same FE regression. The reference categories of education and type of contract consist of employees who attained Year 11 and employees with a permanent contract, respectively. See Figure 4 for additional notes.



(a) Occupation (relative to clerical workers)



(b) Industry (relative to employees in public administration)

Fig. 6. Year-to-year and cumulative relative wage growth by individual characteristics (Equation (2)).
Notes: All graphs in Figures 4-6 are based on the relevant $\beta + \eta_t$ from the same FE regression. The reference categories of occupation and industry consist of clerical employees and employees in public administration, respectively. Several industry categories are left out from Figure 6b to ensure clear graphs. See Figure 4 for additional notes.

The results for the industry indicators in Figure 6b show that employees employed in the economic sectors of mining, supply of utilities, and financial and real estate activities, although the latter's relative wage growth fluctuates considerably and has decreased in recent years, experience the highest wage growth. Conversely, employees in industries focussing on activities in agriculture and accommodation experience the lowest wage growth. Consistent with job search and matching theory, changes in labour demand across industries explain some of the changes in wage growth. For example, the Australian mining industry almost doubled in dollar value over the period 2005 to 2012, which was accompanied by an increased demand for employees in the mining industry. Indeed, mining remained amongst the industries with the highest wage growth. However, industries characterised by increased labour demand could also provide more scope for learning, suggesting potential spillover effects between human capital accumulation and job search as discussed by Bowlus and Liu (2013).

5.2. Sensitivity Analyses

This section presents five sets of robustness checks to assess the sensitivity of our results to changes in the set of independent variables and sample selections.

First, to assess the impact of limiting the analysis to continuing full-time employees on year-to-year wage growth results, we estimate the model underlying the results in Figure 3 (and Table A3) as an FD specification. Using the FD specification (equation (3)) instead of the FE specification (equation (1)) reduces the sample size from 80,625 to 61,507 individual-year observations. Figure B5 in Appendix B shows that the estimated year-to-year wage growth remains very similar, except that in all years (for both nominal and real wages), wage growth estimates obtained through the FD approach are slightly higher. This observation can be explained by the fact that we are now using a slightly more advantaged group of employees: i.e. those who were in full-time work for at least two consecutive years. However, the differences are small, consistent with the finding by Hyslop and Rice (2019) that most of the wage growth in New Zealand over the period 1997 to 2015 is due to continuing employees' wage growth rather than composition changes through employees entering or exiting the labour market.

Second, the composition of the full-time employee population may have changed over time, with more disadvantaged employees leaving employment or moving to part-time employment post-GFC. This may lead to an upward pressure on wage growth, assuming that the exiting employees are characterised by lower wage growth. We re-estimate equation (1) for a sample of full-time and part-time employees together (see Figure B6) and a sample of part-time employees only (see Figure B7), respectively. The results show that including part-time employees as well as observations of employees who transition between part-time and full-time positions leaves the estimated patterns in real and nominal wage growth over time presented in Figure 3 largely unchanged. Figure B7 shows that for part-time employees the level of wage growth is about 1 percentage point lower across all years, although the pattern of wage growth over time is comparable to that of full-time employees. It has a wider confidence interval around its estimated pattern due to the smaller sample size.

Third, we re-estimate equations (1) and (2) adding a dummy for a new entry employee (i.e. the respondent is not observed in full-time employment in year t-1) to investigate differences between "established" full-time employees and new full-time employees. Moreover, we run equations (1) and (2) on a sample that only includes an observation in the analysis if the respondent was observed in full-time work in the previous year, i.e. the same sample that is used for the FD analysis in the first sensitivity check. Our conclusions are robust to this variation, with the key coefficients in our models not changing much. Results are available upon request.

Fourth, we re-estimate a version of equation (1) adding the WPI, AWOTE and AAWI indexes. These results are reported in columns 2 and 6 of Table A3 in Appendix A. The indexes are only significant when occupation and industry are not included; AAWI has the strongest correlation of the three wage indexes. However, none of these indexes add much to the goodness of fit of the model, indicating that no additional information is contained in these indexes once industry and occupation are included in the model.

Fifth, we re-estimate a version of equation (2) adding several transition indicators for job, occupation, industry and contract type. This extension aims to control explicitly for changes in wage growth over time through promotions by recording job, occupation and industry changes. We also include transition indicators for contract type to control for changes in wage growth over time caused by for example employees who switch from a casual contract to a permanent contract, which leads to a loss of their casual wage premium. Adding these transition indicators does not change results much, as all these variables are statistically insignificant. We also add a health variable, indicating the presence of a long-term condition, which might hinder wage growth through for example a lower probability of promotion. Although employees with such a condition are at a lower wage level than healthier employees, it does not seem to affect their year-to-year wage growth. Again, these results are available upon request.

6. Conclusion

As in many other countries, employees in Australia have experienced declining wage growth since the GFC. We use the Australian HILDA Survey data covering the period from 2001 to 2018, to examine how within-individual wage growth of full-time employees is explained by individual characteristics and job characteristics. Moreover, we assess whether the role of employee characteristics in wage growth changed over the period 2001-2018.

This paper adds to the existing literature on wage growth in two ways. First, complementing the macro-oriented literature on the recent low wage growth, we take an individualistic approach examining how wage growth is distributed across employees who differ in individual and job characteristics. Our empirical analysis shows that wage growth seems to a large extent determined by employee characteristics such as age, education, employment contract, occupation and industry. Gender appears less important for wage growth. The employee's age is important for explaining wage growth, consistent with the literature on wage growth over the life cycle that suggests higher wage growth early in the career (i.e. at younger ages) (Bowlus and Liu, 2013; Lagakos et al., 2018). In terms of education, it is especially the university graduates who experience higher wage growth than employees with lower levels of education. The employment contract of an employee is relevant for wage growth mainly through differences between casual and other types of employees, as fixed-term and permanent employees experience a comparable wage growth. Employees in the mining, utilities and financial and real estate sectors experience higher wage growth, while especially employees in the accommodation and agriculture sector tend to lag behind.

Second, we show the extent to which the role of employee characteristics in wage growth changed over the last two decades, possibly because of the business cycle, job polarisation and globalisation. Although the summary statistics show that women have slightly higher wage growth than men post GFC, this disappears (and turns into slightly lower wage growth than men) once we control for individual and job characteristics. Interestingly, we show that the employee's education is most important for wage growth in the pre-GFC period, whereas occupation is particularly relevant in the post-GFC period. This observation suggests decreasing returns to education and an increasing importance of specific occupations, consistent with the literature on job polarisation and increased labour demand for cognitive, non-routine, tasks. Specifically, employees who have occupations that are more cognitive, less routine, such as managers and professionals, experienced relatively high wage growth from 2014 onwards. Moreover, we show that casual employees received higher wage growth pre GFC, but lower wage growth post GFC, once we control for employees' individual and job characteristics. This finding indicates that the returns to insecure –casual– jobs are pro-cyclical and strongly depend on labour demand driven by, for example, cyclical changes to specific economic sectors in the labour market.

The results suggest that wage growth inequality between employees is relatively independent of where the economy is in the business cycle, and that the differences between employees are more substantial than the year-to-year variation. Taken together, our findings are relevant for policy makers, as they inform which subgroups of employees are at risk of lower wage growth.

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Appendices:

Appendix A Additional Tables

Tables A1 and A2 present average wage growth by subgroups for the 2002-2008 versus the 2009-2018 period (roughly pre- and post-GFC). We compare: men versus women, by age, by education level, by income group, by type of contract, by occupation and by industry. We assess whether the role of individual characteristics and job characteristics in wage growth depends on the overall level of wage growth in the population (high versus low), by comparing this role in the period pre- and post-GFC. Table A1 focusses on individuals' characteristics, showing lower percentage wage growth in the post-GFC period than in the pre-GFC period for all groups. However, there are some differences between groups in terms of wage growth. For example, comparing wage growth for men and women over time, Table A1 shows that wage growth, although similar for the two groups, is slightly higher for men pre GFC and slightly higher for women post GFC, with women seemingly suffering less from the downturn in 2008. This pattern can also be observed in Figure B2 of Appendix B for wage growth over time by gender. This pattern is consistent with what is reported in Wilkins et al. (2019) (pp. 62-63).

Younger employees have higher wage growth than older employees. This difference is reduced after the GFC, but younger employees remain having a higher average wage growth than older employees. It seems plausible to suggest that young employees tend to start at the bottom of a pay scale and are thus more likely to receive increments for the first few years of employment, while older employees are more likely to have reached the top of their pay scale. Younger employees are also more likely to experience promotions than older employees. More highly educated employees at higher incomes without long-term health conditions receive higher wage increases than their counterparts, which again decrease post-GFC without changing the pattern of who receives the highest wage growth (except for a few very small changes).

Table A2 focusses on the employment characteristics in our sample, and again we observe that wage growth decreases across the board between the pre- and post-GFC period. Employees on a casual contract receive the highest wage increases, followed by employees on a permanent contract and a fixed-term contract. Again relativities remain the same pre and post GFC. Relativities in pre- and post-GFC average wage growth are not maintained for occupations and industries, where we observe (sometimes large) changes in rankings based on wage growth. For example, sales employees had one of the higher levels of average wage growth pre-2008, and one of the lower wage growth levels post-2008. Similarly, compared to other industries, the rental, hiring and real estate industry experienced a large decrease in wage growth post-2008.

Table A.1
Average year-to-year growth in nominal hourly wages by individual characteristics.

	Time period			
	2002-2008		2009-2018	
	N	Mean wage growth (%)	N	Mean wage growth (%)
Gender:				
Female	7,740	8.748	15,013	7.171
Male	13,759	9.228	24,995	6.811
Age:				
$21 \leq age < 25$ years	1,514	15.00	2,606	11.00
$25 \leq age < 30$ years	2,900	11.69	6,264	8.950
$30 \leq age < 35$ years	3,045	9.527	5,518	8.013
$35 \leq age < 40$ years	2,942	8.914	4,701	6.925
$40 \leq age < 45$ years	3,230	7.600	4,907	6.012
$45 \leq age < 50$ years	3,208	7.471	5,104	5.854
$50 \leq age < 55$ years	2,547	7.581	5,040	5.025
$55 \leq age < 60$ years	1,551	6.977	3,962	5.391
$60 \leq age < 65$ years	562	7.444	1,906	5.425
Education:				
Year 11	4,313	7.533	5,675	5.912
Year 12	2,938	9.707	5,440	7.298
Cert III and IV	5,281	9.160	10,533	6.408
Diploma and adv. diploma	2,244	8.247	4,416	6.942
Bachelor, grad and postgrad	6,723	9.934	13,944	7.638
Household situation:				
Partner	15,316	8.885	29,433	6.862
No partner	6,183	9.475	10,575	7.181
Own resident children	9,745	8.444	18,131	6.239
No own resident children	11,754	9.561	21,877	7.532
Background:				
Indigenous origin	284	9.784	694	6.329
Not of Indigenous origin	21,215	9.045	39,314	6.957
Born abroad	4,514	9.152	7,984	6.641
Not born abroad	16,985	9.029	32,024	7.022
Individual's income:				
First quintile	3,077	8.799	5,921	5.844
Second quintile	4,359	8.787	8,144	6.622
Third quintile	4,582	9.048	8,539	7.111
Fourth quintile	4,798	8.861	8,791	7.260
Fifth quintile	4,683	9.677	8,613	7.527
Health status:				
Long-term health condition	2,911	8.303	5,799	5.646
No long-term health condition	18,588	9.173	34,209	7.167

Notes: The number of observations and mean wage growth are provided at the individual-year level. The time period under observation is from 2002 to 2018 with N=61,507. Note that the individual's income quintiles are based on the sample with 80,625 observations.

Table A.2
Average year-to-year growth in nominal hourly wages by job characteristics.

	Time period			
	2002-2008		2009-2018	
	N	Mean wage growth (%)	N	Mean wage growth (%)
Type of contract:				
Permanent contract	5,281	9.160	10,533	6.408
Fixed-term contract	4,313	7.533	5,675	5.912
Casual contract	2,938	9.707	5,440	7.298
Occupation:				
Managers	3,134	9.029	6,818	7.240
Professionals	5,865	10.09	11,103	7.937
Technicians and trades	3,267	10.08	6,003	7.658
Community and personal service	1,422	8.519	2,796	6.593
Clerical and admin	3,546	7.272	5,960	5.996
Sales	1,074	9.808	1,815	5.436
Machinery operators and drivers	1,824	8.187	3,203	5.236
Labourers	1,367	7.974	2,310	5.903
Job industry:				
Agriculture, forestry and fishing	395	7.797	489	6.008
Mining	533	12.09	1,124	9.251
Manufacturing	3,131	8.759	4,365	5.863
Electricity, gas and water service	323	10.66	718	7.509
Construction	1,281	11.09	3,176	7.787
Wholesale trade	954	7.960	1,746	5.394
Retail trade	1,377	8.410	2,522	5.846
Accommodation and food service	562	8.429	980	4.913
Transportation and storage	1,133	8.749	2,201	6.295
Information and communication	721	8.788	907	7.529
Financial and insurance	995	8.706	1,980	8.079
Rental, hiring and real estate	263	14.00	593	6.625
Professional, scientific and technical	1,527	11.27	3,172	7.475
Administrative and support service	393	9.778	897	7.457
Public administration and safety	2,550	8.691	4,444	7.507
Education and training	2,349	8.168	4,300	6.965
Human health and social work	2,042	7.998	4,614	7.184
Arts and recreation service	313	8.956	556	6.799
Other service activities	657	9.194	1,224	7.051

Notes: The number of observations and mean wage growth are provided at the individual-year level. The time period under observation is from 2002 to 2018 with N=61,507.

Table A.3
Estimated coefficients of employee characteristics in nominal wage model (Equation (1)).

	Log hourly wage					
	(1)	(2)	(3)	(4)	(5)	(6)
Demographic characteristics:						
Age: reference group is $21 \leq age < 25$ years						
$25 \leq age < 30$ years	0.0728	0.0741***	0.0735***	0.0695***	0.0668***	0.0685***
	(0.0052)	(0.0053)	(0.0052)	(0.0052)	(0.0051)	(0.0051)
$30 \leq age < 35$ years	0.1176***	0.1204***	0.1184***	0.1126***	0.1097***	0.1127***
	(0.0077)	(0.0078)	(0.0077)	(0.0076)	(0.0075)	(0.0076)
$35 \leq age < 40$ years	0.1236***	0.1260***	0.1244***	0.1181***	0.1171***	0.1193***
	(0.0096)	(0.0097)	(0.0096)	(0.0095)	(0.0094)	(0.0095)
$40 \leq age < 45$ years	0.1065***	0.1079***	0.1071***	0.1018***	0.1020***	0.1032***
	(0.0113)	(0.0114)	(0.0113)	(0.0112)	(0.0112)	(0.0113)
$45 \leq age < 50$ years	0.0725***	0.0748***	0.0729***	0.0686***	0.0685***	0.0702***
	(0.0130)	(0.0131)	(0.0130)	(0.0129)	(0.0129)	(0.0130)
$50 \leq age < 55$ years	0.0282*	0.0303**	0.0286*	0.0265*	0.0250*	0.0259*
	(0.0147)	(0.0148)	(0.0147)	(0.0146)	(0.0146)	(0.0147)
$55 \leq age < 60$ years	-0.0176	-0.0171	-0.0173	-0.0173	-0.0194	-0.0203
	(0.0168)	(0.0169)	(0.0168)	(0.0167)	(0.0167)	(0.0168)
$60 \leq age < 65$ years	-0.0599***	-0.0593***	-0.0599***	-0.0572***	-0.0600***	-0.0610***
	(0.0192)	(0.0193)	(0.0192)	(0.0191)	(0.0191)	(0.0192)
Education: reference group is < Year 12						
Year 12	-0.0378**	-0.0360*	-0.0378**	-0.0339*	-0.0317*	-0.0305*
	(0.0190)	(0.0188)	(0.0190)	(0.0187)	(0.0184)	(0.0182)
Cert III and IV	-0.0031	-0.0022	-0.0031	-0.0021	-0.0015	0.0000
	(0.0136)	(0.0132)	(0.0136)	(0.0134)	(0.0134)	(0.0130)
Diploma and adv. diploma	0.0209	0.0185	0.0212	0.0211	0.0248	0.0220
	(0.0178)	(0.0170)	(0.0178)	(0.0176)	(0.0174)	(0.0166)
Bachelor, grad and postgrad	0.0435**	0.0454**	0.0437**	0.0394*	0.0366*	0.0380*
	(0.0213)	(0.0210)	(0.0213)	(0.0210)	(0.0206)	(0.0203)
Wage indexes:						
WPI		0.0068***				-0.0000
		(0.0020)				(0.0020)
AWOTE		0.0001				-0.0000
		(0.0003)				(0.0003)
AAWI		0.0084**				-0.0040
		(0.0033)				(0.0037)
Job characteristics:						
Contract type: reference group is permanent contract						
Fixed-term contract			0.0086**	0.0073*	0.0081**	0.0081**
			(0.0039)	(0.0038)	(0.0038)	(0.0038)
Casual contract			0.0158***	0.0201***	0.0209***	0.0190***
			(0.0059)	(0.0058)	(0.0057)	(0.0058)
Occupation: reference group is clerical and admin						
Managers				0.0448***	0.0425***	0.0431***
				(0.0051)	(0.0050)	(0.0051)
Professionals				0.0302***	0.0295***	0.0288***
				(0.0052)	(0.0051)	(0.0051)
Technicians and trades				0.0240***	0.0235***	0.0205***
				(0.0068)	(0.0068)	(0.0068)
Community and personal service				-0.0046	-0.0040	-0.0042
				(0.0086)	(0.0084)	(0.0084)
Sales				-0.0036	-0.0039	-0.0038
				(0.0071)	(0.0070)	(0.0070)
Machinery operators and drivers				0.0069	0.0053	0.0043
				(0.0080)	(0.0078)	(0.0080)
Labourers				0.0060	0.0059	0.0056
				(0.0080)	(0.0079)	(0.0082)

Table A.3 (Continued)

	Log hourly wage					
	(1)	(2)	(3)	(4)	(5)	(6)
Job characteristics (Continued):						
Industry: reference group is public admin and safety						
Agriculture, forestry and fishing				-0.0912***	-0.0812***	
				(0.0175)	(0.0171)	
Mining				0.1201***	0.1147***	0.1110***
				(0.0167)	(0.0160)	(0.0160)
Manufacturing				-0.0185**	-0.0176**	-0.0184**
				(0.0090)	(0.0088)	(0.0089)
Electricity, gas, water and water supply				0.0262	0.0255	0.0266
				(0.0168)	(0.0164)	(0.0164)
Construction				0.0069	0.0066	0.0087
				(0.0093)	(0.0091)	(0.0099)
Wholesale trade				-0.0501***	-0.0484***	-0.0474***
				(0.0095)	(0.0093)	(0.0093)
Retail trade				-0.0845***	-0.0807***	-0.0830***
				(0.0101)	(0.0098)	(0.0101)
Accommodation and food service activities				-0.0881***	-0.0815***	-0.0824***
				(0.0124)	(0.0124)	(0.0127)
Transportation and storage				-0.0296***	-0.0275***	-0.0246**
				(0.0105)	(0.0102)	(0.0101)
Information and communication				-0.0077	-0.0062	-0.0077
				(0.0128)	(0.0127)	(0.0128)
Financial and insurance activities				0.0023	0.0033	0.0023
				(0.0118)	(0.0117)	(0.0117)
Rental, hiring and real estate activities				-0.0923***	-0.0864***	-0.0872***
				(0.0152)	(0.0148)	(0.0148)
Professional, scientific and technical activities				-0.0327***	-0.0314***	-0.0306***
				(0.0084)	(0.0083)	(0.0082)
Administrative and support service activities				-0.0538***	-0.0520***	-0.0519***
				(0.0096)	(0.0095)	(0.0096)
Education and training				-0.0469***	-0.0418***	-0.0397***
				(0.0119)	(0.0118)	(0.0118)
Human health and social work activities				-0.0279***	-0.0249***	-0.0250***
				(0.0089)	(0.0088)	(0.0088)
Arts and recreation service activities				-0.0626***	-0.0569***	-0.0584***
				(0.0136)	(0.0134)	(0.0134)
Other service activities				-0.0667***	-0.0655***	-0.0686***
				(0.0103)	(0.0101)	(0.0102)

Table A.3 (Continued)

	Log hourly wage					
	(1)	(2)	(3)	(4)	(5)	(6)
Business cycle effects (including inflation): reference year is 2001						
Year 2002	0.0437***	0.0448***	0.0437***	0.0433***	0.0440***	0.0460***
	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0044)
Year 2003	0.0924***	0.0910***	0.0925***	0.0925***	0.0937***	0.0952***
	(0.0049)	(0.0050)	(0.0049)	(0.0049)	(0.0049)	(0.0050)
Year 2004	0.1410***	0.1375***	0.1414***	0.1397***	0.1418***	0.1437***
	(0.0052)	(0.0054)	(0.0052)	(0.0052)	(0.0052)	(0.0054)
Year 2005	0.1985***	0.1930***	0.1987***	0.1970***	0.1995***	0.2026***
	(0.0055)	(0.0057)	(0.0055)	(0.0054)	(0.0055)	(0.0057)
Year 2006	0.2623***	0.2558***	0.2626***	0.2605***	0.2637***	0.2662***
	(0.0059)	(0.0061)	(0.0059)	(0.0058)	(0.0058)	(0.0061)
Year 2007	0.3352***	0.3301***	0.3357***	0.3324***	0.3357***	0.3377***
	(0.0062)	(0.0064)	(0.0062)	(0.0062)	(0.0062)	(0.0064)
Year 2008	0.3974***	0.3915***	0.3979***	0.3931***	0.3971***	0.3996***
	(0.0066)	(0.0068)	(0.0066)	(0.0065)	(0.0065)	(0.0068)
Year 2009	0.4479***	0.4417***	0.4484***	0.4438***	0.4480***	0.4513***
	(0.0069)	(0.0071)	(0.0069)	(0.0069)	(0.0069)	(0.0071)
Year 2010	0.4998***	0.4997***	0.5003***	0.4951***	0.4990***	0.5013***
	(0.0074)	(0.0075)	(0.0074)	(0.0073)	(0.0073)	(0.0074)
Year 2011	0.5473***	0.5456***	0.5478***	0.5418***	0.5462***	0.5487***
	(0.0076)	(0.0077)	(0.0076)	(0.0076)	(0.0075)	(0.0076)
Year 2012	0.5889***	0.5879***	0.5894***	0.5831***	0.5879***	0.5914***
	(0.0080)	(0.0080)	(0.0080)	(0.0079)	(0.0078)	(0.0079)
Year 2013	0.6243***	0.6279***	0.6249***	0.6180***	0.6215***	0.6248***
	(0.0084)	(0.0085)	(0.0084)	(0.0083)	(0.0083)	(0.0083)
Year 2014	0.6576***	0.6665***	0.6582***	0.6511***	0.6546***	0.6568***
	(0.0088)	(0.0090)	(0.0088)	(0.0087)	(0.0087)	(0.0089)
Year 2015	0.6941***	0.7060***	0.6948***	0.6878***	0.6915***	0.6926***
	(0.0092)	(0.0095)	(0.0092)	(0.0091)	(0.0090)	(0.0093)
Year 2016	0.7324***	0.7480***	0.7332***	0.7256***	0.7301***	0.7307***
	(0.0096)	(0.0101)	(0.0096)	(0.0095)	(0.0095)	(0.0100)
Year 2017	0.7707***	0.7882***	0.7714***	0.7636***	0.7684***	0.7684***
	(0.0100)	(0.0107)	(0.0100)	(0.0099)	(0.0099)	(0.0106)
Year 2018	0.8147***	0.8339***	0.8157***	0.8073***	0.8127***	0.8118***
	(0.0105)	(0.0112)	(0.0105)	(0.0104)	(0.0103)	(0.0112)
Number of observations	80,625	79,336	80,625	80,625	80,625	79,336
Number of individuals	11,714	11,610	11,714	11,714	11,714	11,610
R^2	0.5000	0.5021	0.5001	0.5074	0.5154	0.5168
SA3 regional area FE	No	No	No	No	Yes	Yes

Notes: Each column reports the output for a different FE regression. Parameter estimates are reported. Clustered (by individual) standard errors are in parentheses. ***,**,*, correspond to significance levels of 1%, 5%, 10%, respectively. The regressions include zero-one indicator variables for number of household members (3), marital status (5), number of own resident children (3), private sector and the SA3 regional location of the household (323). The year effects provided in Column 5 are used for Figure 3 and Figure B3 (nominal growth).

Appendix B Additional Figures

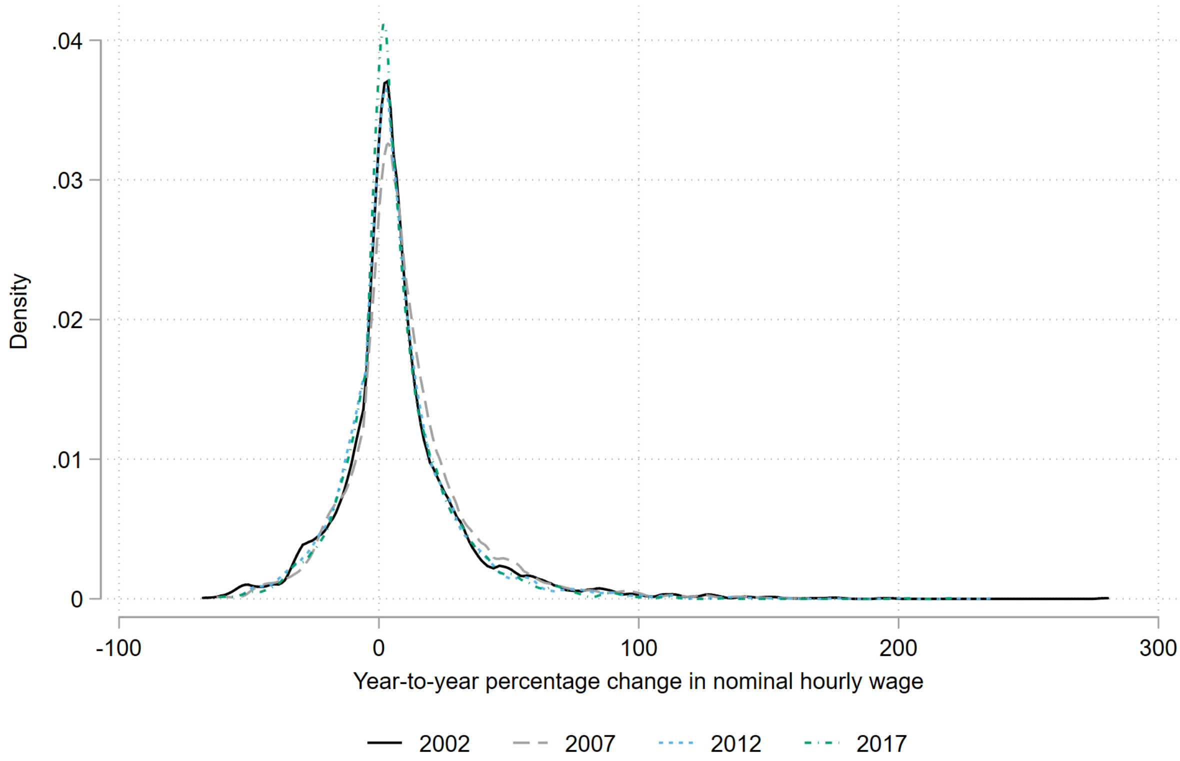


Fig. B.1. Year-specific density plot of percentage change in nominal hourly wages.
Notes: N=61,507.

Fig. B.2. Year-to-year growth in median weekly nominal hourly wages over time by gender.
Notes: N=61,507.

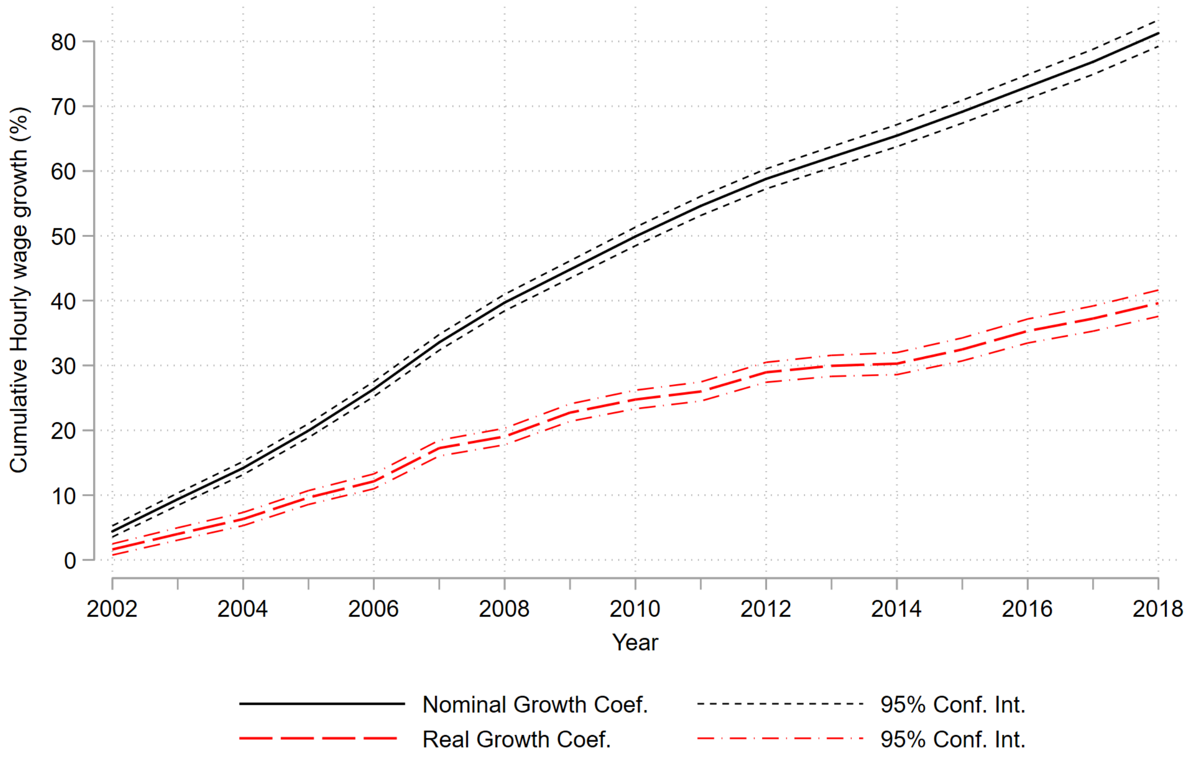
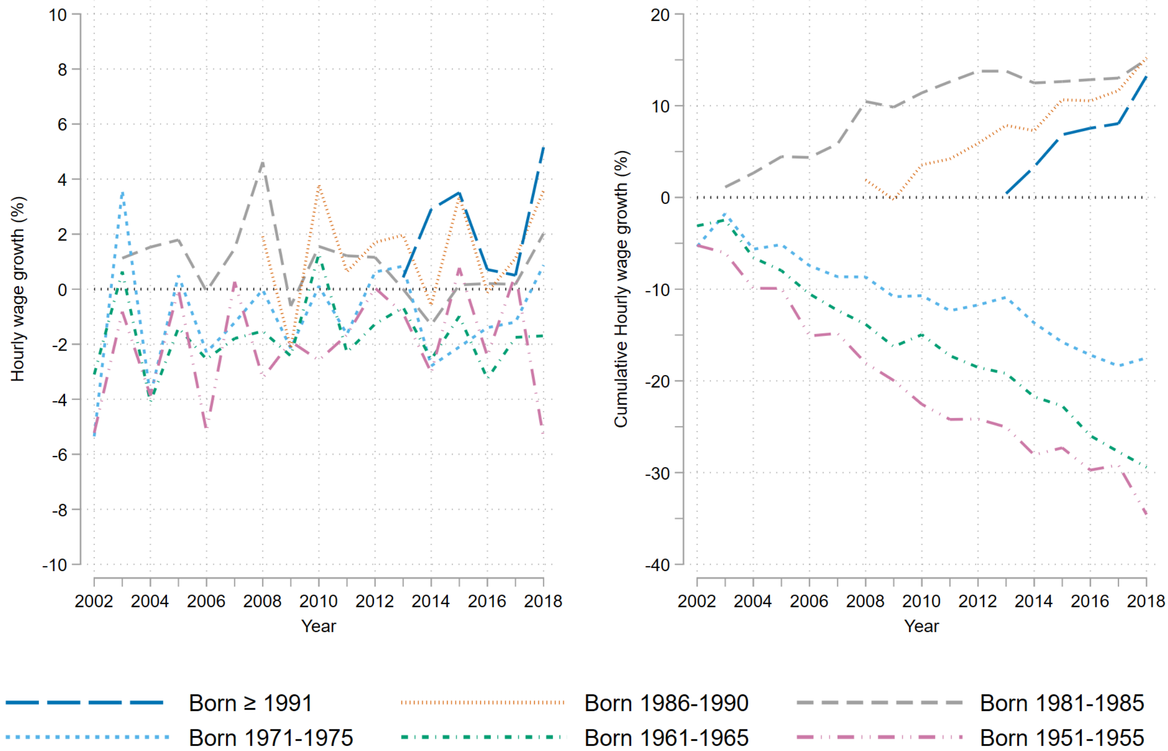


Fig. B.3. Cumulative wage growth (Equation (1)).
Notes: N=80,625. See Figure 3 for additional notes.



(a) Birth cohort (relative to people born in 1976-1980)

Fig. B.4. Year-to-year and cumulative relative wage growth by birth cohort (Equation (2)).

Notes: This graph is based on the same empirical model as Figures 4-6, except that the variables that represent the employee's age are replaced by the employee's birth cohort. The relevant $\beta + \eta_t$ from the FE regression are provided. The reference categories of the birth cohort and year variables consist of people born in 1976-1980 and of the year 2001, respectively. The reference category of the year variable is different for the (more recent) birth cohorts born in 1981-1985, born in 1986-1990 and born after 1990, and is the year 2002, 2007 and 2012, respectively. Several birth cohort categories are left out from Figure B4 to ensure clear graphs. The sample of analysis includes 80,625 individual-year observations and 11,714 unique individuals.R^2 of the regression equals 0.53. See Figure 4 for additional notes.

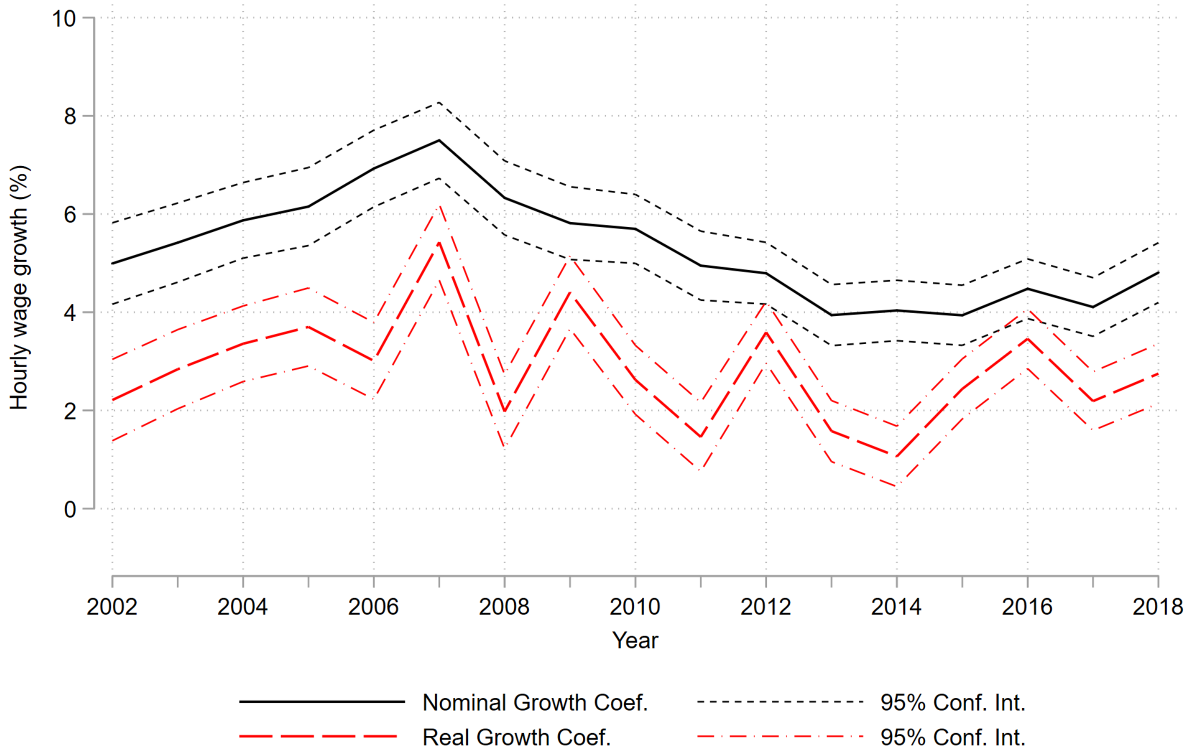


Fig. B.5. Year-to-year wage growth (Equation (3)).
Notes: The graphs are based on the nominal and real wage coefficients estimated in an FD regression (available upon request from the authors). The 95% confidence intervals are computed using clustered standard errors by individual employees. The regressions include zero-one indicator variables for age (8), education (4), number of household members (3), marital status (5), number of own resident children (3), type of contract (2), job occupation (7), job industry (18), private sector and the SA3 regional location of the household (319). The sample of analysis includes 61,507 individual-year observations and 11,099 unique individuals. R^2 equals 0.073 and 0.034 for the nominal and real wage growth model, respectively.

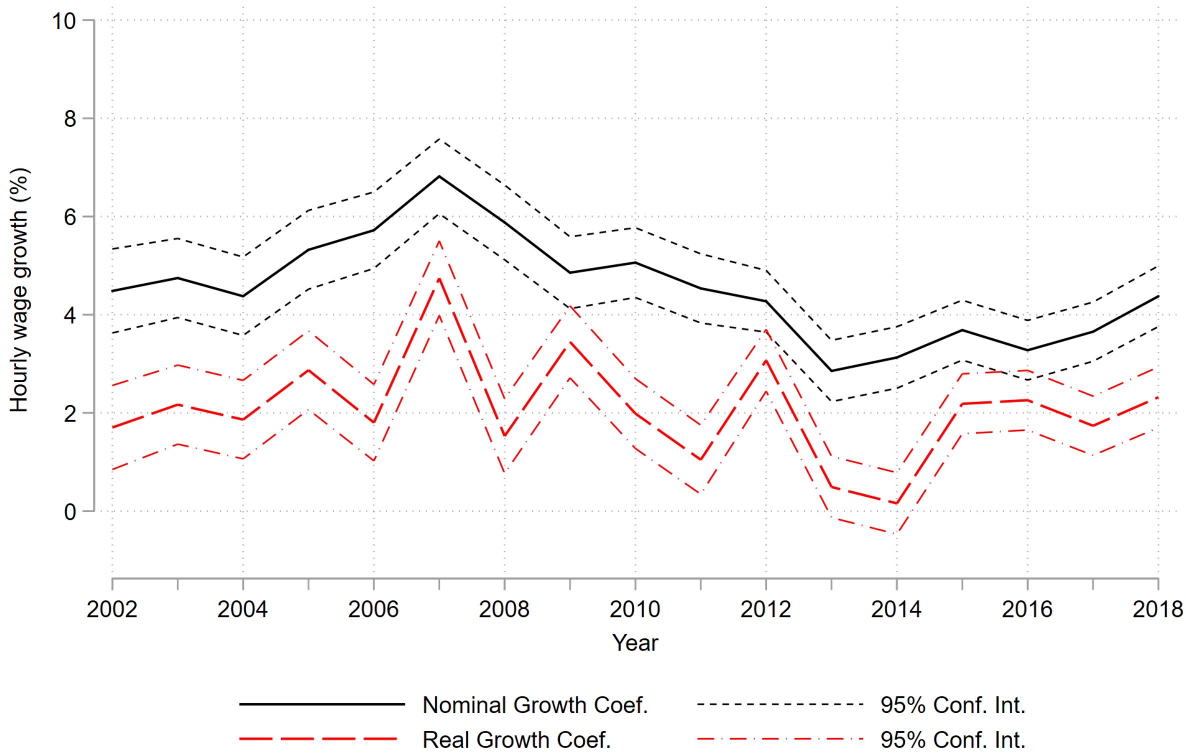


Fig. B.6. Year-to-year wage growth (Equation (1)). Sample of full-time and part-time employees.
Notes: The nominal and real wage coefficients are based on two sets of FE regressions. The 95% confidence intervals are computed using clustered standard errors by individual. See Figure 3 for additional notes. The regressions include an additional zero-one indicator variable for full-time/part-time status. The sample of analysis includes 111,246 individual-year observations and 14,736 unique individuals. R^2 equals 0.46 and 0.20 for the nominal and real wage growth model, respectively.

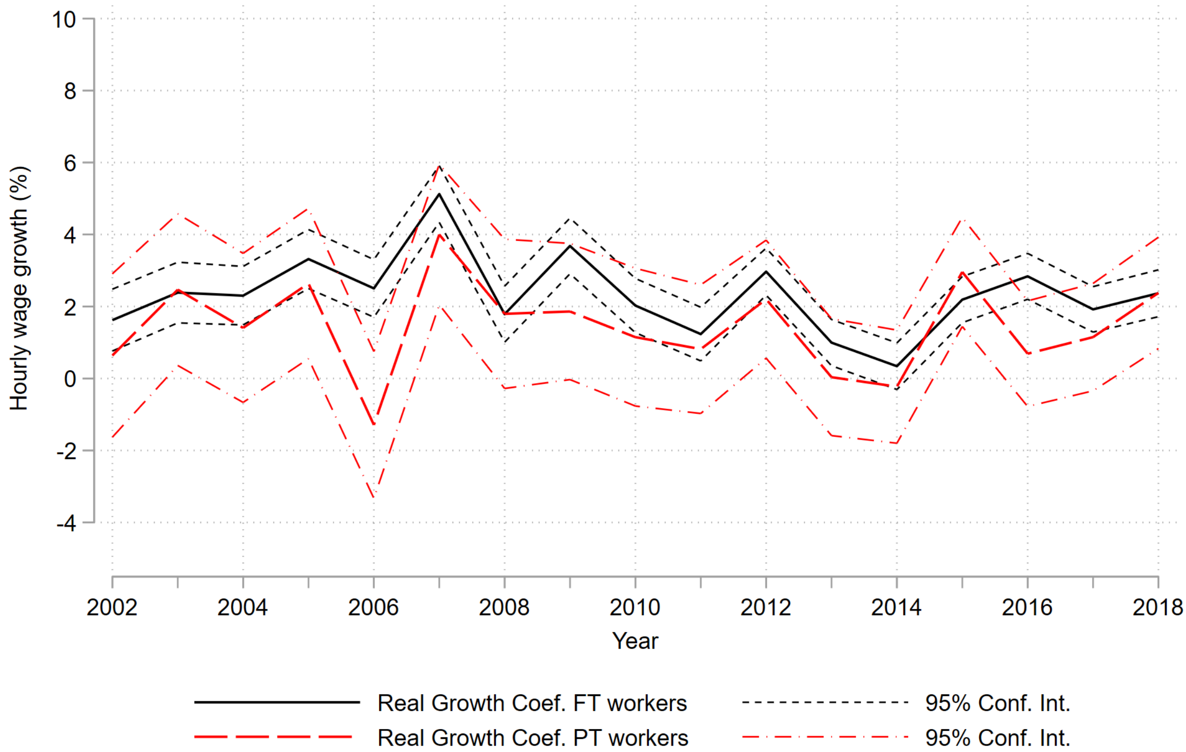


Fig. B.7. Year-to-year wage growth for full-time and part-time employees separately (Equation (1)).
Notes: The real wage coefficients are based on two sets of FE regressions, estimated separately for full-time employees and part-time employees. The 95% confidence intervals are computed using clustered standard errors by individual. See Figure 3 for additional notes. The sample of analysis includes for the full-time employees 80,625 individual-year observations and 11,714 unique individuals and for the part-time employees 25,784 individual-year observations and 5,416 unique individuals. R^2 equals 0.23 and 0.12 for the full-time and part-time real wage growth model, respectively.