Measuring Labour Quality in (Closer to) Real Time Using Emerging Microdata Sources

Angelina Bruno*, Jonathan Hambur** and Lydia Wang*

Paper for Joint ABS-RBA Conference on "Human Capital"

June 2024

*Economic Analysis Department
**Economic Research Department
Reserve Bank of Australia

The authors would like to thank Derek Burnell, Thai Nguyen and Pengfei Zhao. Thank you to the Australian Bureau of Statistics for organising this conference and for all their hard work providing the data used in this paper. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Reserve Bank of Australia. The authors are responsible for any errors.

Authors: BrunoA@rba.gov.au, HamburJ@rba.gov.au, WangLy@rba.gov.au

DRAFT

Abstract

One explanation put forward for recent weakness in productivity is the entry of less experienced workers to the labour market. Unfortunately, existing labour 'quality' statistics that attempt to capture such dynamics use lagged information, extrapolating out past patterns. This could give a misleading view of developments, particularly in the context of recent unusual labour market dynamics. To understand whether this is the case, and whether this has implications for our understanding of recent productivity outcomes, we use microdata sources to construct timely labour quality statistics. We also explore whether newly integrated administrative datasets can be used to consider additional dimensions of labour 'quality', and could therefore be used to improve labour quality statistics going forwards. Overall, we find evidence that labour quality has increased since COVID-19, though at a slower rate than implied by traditional statistics. This has contributed to much of the growth in market services productivity over the period.

JEL Classification Numbers: E24

Keywords: productivity; skills; human capital

Table of Contents

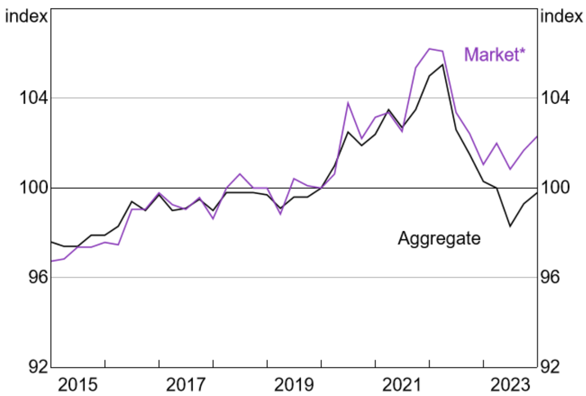
1. Introduction

Productivity growth is an important concept. It is a key driver of economic growth, and therefore fiscal balance and living standards over the medium term. Moreover, over the shorter term it will be an important driver of economic capacity: if productivity growth is slower, the economy will only be able to sustain a slower rate of growth before inflation picks up. As such, it is important for policymakers to understand productivity growth and its drivers.

The current circumstances are no exception. Productivity has been volatile over the past few years (Bruno, Dunphy and Georgiakakis 2023; Figure 1). But looking through this volatility, productivity growth has been fairly slow, averaging around 0 per cent for the whole economy and 0.4 per cent for the market sector over the four years to December 2023. Understanding the causes of this slow growth is extremely important, as it can help us to understand whether it will continue.

Figure 1: Labour Productivity

Levels, December 2019 = 100



Source: ABS, Authors' calculations

One explanation that has been put forward for the slow rate of productivity growth over recent years is that strong conditions have drawn younger, less educated or less experienced workers into the labour force (Productivity Commission 2023). As these workers have fewer skills and less accumulated 'human capital', they may be less productive, and so their entry to the labour market may lower aggregate productivity.

One way to assess whether this has affected productivity outcomes is to use quality-adjusted labour input indices. Labour productivity captures how much output we produce for a set of labour inputs. Mechanically this is measured as the ratio of gross domestic product (GDP) (output) to total hours worked in the economy (inputs). However, not all hours are necessarily the same. If some workers have fewer skills, experience, and human capital they may tend to be less productive. In thinking about the extent of labour inputs being used, we could potentially place lower weights on the hours worked by these workers to capture the fact that those hours are 'worth' less. Doing so leads to an index of labour inputs that is adjusted for labour 'quality', the inherent human capital held by workers. Comparing this to total hours worked can then provide a sense of how changes in 'quality' of labour may be influencing aggregate productivity.

The Australian Bureau of Statistics (ABS) already constructs and reports on such measures, which can provide valuable insights (ABS 2005; 2022). However, the published ABS index currently relies on quite lagged data taken from five-yearly Censuses. Data between Censuses are interpolated, and trends are extrapolated for periods after the most recent Census. In normal times this approach is likely to be effective, given demographic and other related trends that will determine human capital will tend to be slow moving. However, during exceptional periods, such as the past few years, this could lead to misleading results.

One potential solution to this issue is to try to leverage the timely microdata sets that have emerged over the past five or so years. In this paper we do exactly that, leveraging the Longitudinal Labour Force Survey (LLFS), Person Level Integrated Data Asset (PLIDA) and Single Touch Payroll (STP) datasets to construct more timely measures of labour quality. These can help us to understand recent productivity outcomes. We also show how the integration of these various datasets together potentially allows us to build 'better' labour quality indices that capture additional important factors that determine human capital, such as their time outside of the labour force.

Using existing approaches to measuring labour quality (based only on age and education) but more frequent data, we find that the share of hours worked by more educated workers has actually increased relative to pre-COVID-19, suggesting that labour quality has increased rather than declined. That said, the increase is smaller than that implied by the published statistics. Taking the results at face value, they suggest that a sizeable portion of the growth in productivity in market sector over this period reflected improvements in the skills and human capital of the labour force. Or putting it another way, if labour quality had not increased, productivity growth would potentially have been even slower.

Implicitly, this calculation assumes that increases in human capital flowed through to increased productivity in a similar way to history, which may or may not be the case. It also abstracts from the possibility that these changes in labour quality could be offset by worse job matching – for example, if the additional highly educated workers were employed in lower-skill jobs where their education was not helpful. As such, we should interpret these estimates of the effect on productivity with some caution. But still, it does suggest that changes in labour quality if anything contributed to productivity growth over the period, potentially substantially.

We also find that several characteristics that are not included in the official or our higher-frequency *quality adjusted* labour input (QALI) indices can play an important role in determining a works human capital. In particular, we find that a worker's tenure at their job, and whether they have spent some time on unemployment benefits or out of employment are important predictors of their human capital. We are only able to consider these characteristics due to the recent integration of various administrative datasets to the Census data.

Using these integrated datasets we also find that the share of workers with time on unemployment benefits or outside of the labour force has increased slightly over the past two years. This means that standard QALI indices may overstate the growth human capital in the labour force. That said, the increases in the share of workers with such characteristics are small, and so it appears unlikely that this would change the overall findings from above.

Overall, our findings suggest that the increasing availability of detailed and timely microdata sets can potentially allow for significant improvements in our ability to measure human capital and labour quality in real-time, and therefore interpret productivity developments. Further integrations, such as the integration of the LLFS with STP, could increase this value even further.

The rest of the paper is laid out as follows. In Section 2 of this paper, we discuss the current ABS approach to quality estimation. In the Section 3, we apply ABS methodology to more timely data in LLFS microdata. In Section 4, we extend existing human capital measurement approaches to consider other factors that could indicate a worker's productivity using integrated microdata sources, before concluding.

2. Current Approaches to Labour Quality Adjustment

As noted above, productivity statistics measure how much output is produced, compared to the number of inputs used. In constructing headline productivity statistics, the ABS uses a simple measure of labour inputs: the sum of all hours worked.[1] This implicitly assumes all workers can produce the same amount in an hour, no matter their education, experience or other characteristics.

From 2005, the ABS developed a *quality-adjusted* measure of labour inputs (QALI) (ABS 2005). This QALI index is intended to account for changes in the composition of the workforce that may be associated with a substantial change in the human capital of the labour force. So if the total number of hours worked in the economy stays the same, but more of them are worked by highly educated workers with lots of human capital and therefore higher productivity, the QALI index will increase to account for the increase in the quality of the hours being worked, while the total hours index will remain unchanged. The difference in the two captures changes in the quality or human capital of the labour force. Using the QALI index to deflate GDP (i.e. as the labour input), rather than total hours, provides a quality-adjusted measure of labour productivity that abstracts from the effect of changes in the composition and human capital of the labour force.

To construct QALI measures the ABS focuses on two determinants of worker human capital and productivity: their age (a proxy for experience) and their education. To do this they use Census data to assess the effect of these factors on worker wages, which are taken to be a good proxy of their productivity. They also use Census data to calculate the total hours worked by cohorts, based on their age and education.[2] The hours and wages information are then combined to construct a Tornqvist index of labour inputs.[3]

As this approach relies on the 5-yearly Census, the ABS has to take an approach to interpolating between observations and extrapolating out past the most recent observation. For the former, the ABS linearly interpolates outcomes between Census years. For the latter, the ABS extrapolates trends observed over the most recent 5 years out.

Over time, the QALI index has tended to grow more quickly than total hours worked (Figure 2). This reflects increases in the share of hours accruing to more educated workers. The increase in

---

1 By headline productivity statistics, we mean labour and multifactor productivity (MFP) statistics typically discussed in most ABS publications and by most data user agencies. These headline statistics rarely feature quality-adjusted measures of labour productivity and MFP.

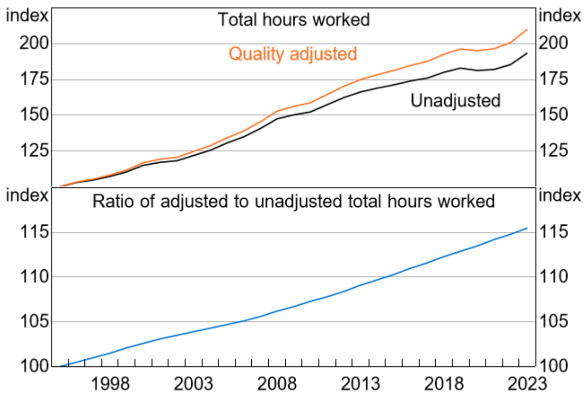
2 Gender is also considered in the construction of the index, but is not the main focus of this paper.

3 For more details, please see Annex B, Chapter 19 of ABS (2021).

the 'quality' of the labour force has been an important factor driving productivity according to this approach. In particular, if we use the QALI index as our measure of labour inputs, rather than total hours, productivity is substantially lower: growth in the quality of labour inputs accounts for around one-third of the growth in productivity in the market sector, since the mid-1990s, or around ½ percentage points per year (Figure 3). The contribution of labour quality, or growth in human capital, has ticked up slightly over time.

Figure 2: Labour Input Indices

1994/95 = 100

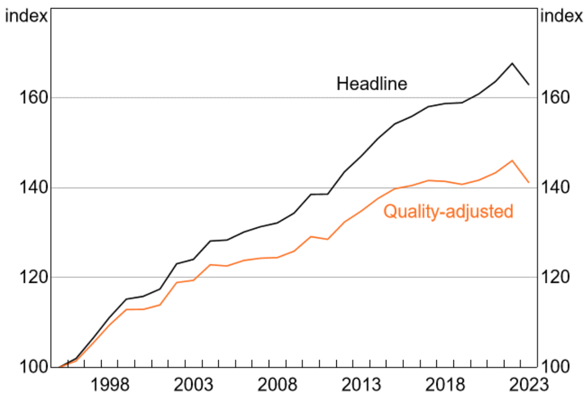


Notes: Market sector.

Sources: ABS; Authors' calculations.

Figure 3: Labour Productivity

1994/95 = 100



Note: Market sector.

Sources: ABS; Authors' calculations.

While QALI-adjusted productivity data are not actively used in headline productivity statistics, they are often used to assess the contribution from changing labour quality or 'labour composition' to headline productivity and economic growth (D'Arcy and Gustafsson 2012; Duretto, Majeed and Hambur 2022). Given the indices are fairly simple, such calculations should be interpreted with some caution. But they can still provide a useful sense of how human capital could be contributing to productivity growth.

3. Constructing a Timely QALI Index Using the LLFS Data

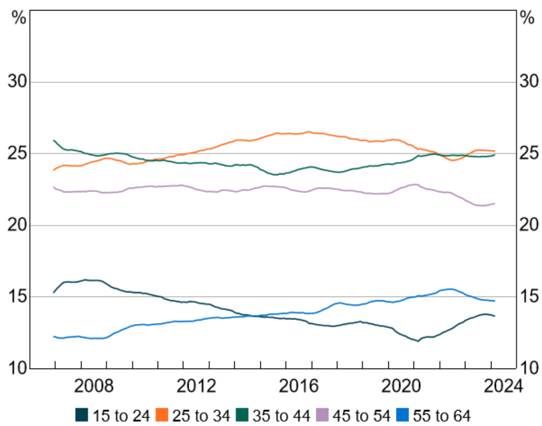
To overcome the issue of timeliness in the official QALI index, we turn to the person-level LLFS microdata asset. This dataset contains de-identified person-level responses to the ABS Labour Force Survey at a monthly frequency. It contains information on hours worked, education, age and other characteristics. As such, it contains all the information we need in order to replicate the official ABS index at a higher frequency.

As discussed before, there are two key components in the QALI index. The wage rate for different groups, which reflect their productivity level, and the share of hours worked by different groups. The former we take directly from the official index. For the latter we construct measures of the share of hours worked by different age and education cohorts using the LLFS. In doing so we focus on the market sector, to align with the official QALI index. Our measure of hours worked is monthly actual hours worked in all jobs.

Figures 4 and 5 show some of the compositional trends coming out of the data. Consistent with Brown and Guttmann (2017), older workers have accounted for a growing share of the labour force over time. Over the COVID-19 period there were some further shifts, with the share of very young workers (aged 15–24 years old) falling then rebounding, while the share of older prime aged workers (45–54) falling sharply.[4]

Figure 4: Hours Worked in All Jobs

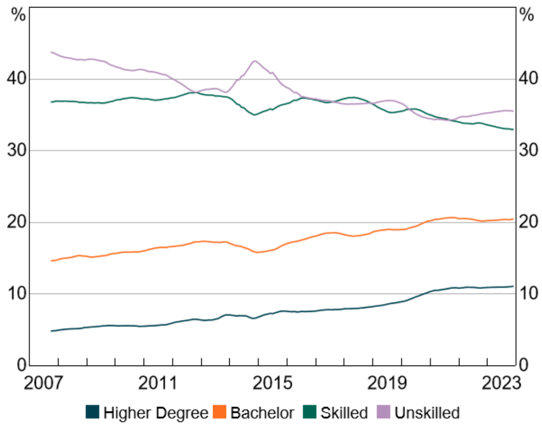
By age group, 12-month moving average



Sources: ABS; Authors' calculations.

4 The tick up in the share of very young workers may in part reflect the brief 'baby boom'; that occurred in the mid-2000s to mid-2010s, with many of these children entering the labour market over the coming years (Australian Treasury 2023).

Figure 5: Hours Worked in All Jobs
By education level, 12-month moving average



Sources: ABS; Authors' calculations.

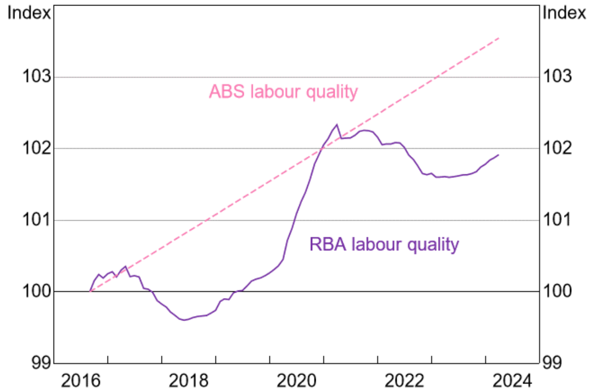
Focusing on education, as noted earlier the share of more educated workers in the labour force has increased over time. Over the COVID-19 period there was a further shift up in the share hours worked by those with Bachelors degrees or higher. This was offset by a fall in the number of Skilled (workers with non-university post-secondary) and Unskilled (secondary equivalent education or lower), likely at least in part reflecting disruption in many contact-intensive industries during COVID-19 (Bruno, Dunphy and Georgiakakis 2023). The hours share of unskilled workers started to recover in mid-2022 but are yet to recover to pre-pandemic levels.

These patterns are interesting. But it is hard to assess how they could affect the overall productivity of the labour force. Incorporating them into a QALI index can provide a framework to assess the net effects.

We construct our QALI index by using the wages data used in the official QALI index, and applying the same Tornqvist index methodology to the LLFS hours worked data. We then take a 12-month moving average and index to August 2016 to smooth out seasonal volatility.

Figure 6 compares this higher frequency index to the published index. The two are very similar in mid-2016 and mid-2021, the dates of the Censuses underlying the official index. This provides a good check that our approach is capturing the same underlying information. However, the patterns look very different between and after the Census dates. While the official index interpolates linearly between 2016 and 2021, our index shows that growth in labour quality was slow over the years leading up to COVID-19. It then increased sharply over 2020, catching up to the official index. This likely reflects the level shift up in the share of hours worked by higher educated workers noted above. After peaking in 2021, our QALI index then declined slightly over 2022 and 2023, before ticking up in 2024. This is in stark contrast to the official index, which assumes that labour quality continued to grow at a fast rate. So overall, according to our higher-frequency QALI index, labour quality actually increased over the COVID-19 period, rather than decreasing as some have argued, though the increase was smaller than implied by the official index.

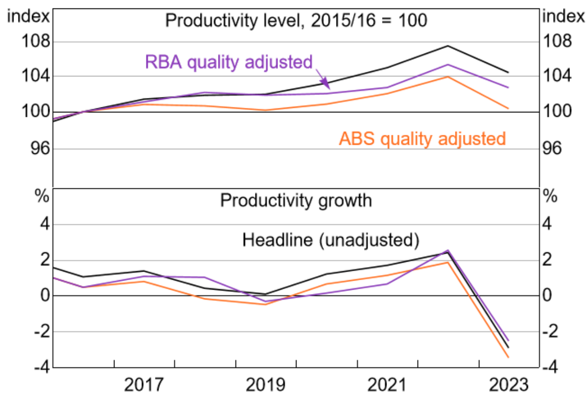
Figure 6: Labour Quality Indices
August 2016 = 100



Notes: Market sector.
Sources: ABS; Authors' calculations.

This has direct implications for our understanding of developments in productivity. Using our QALI index as the measure of labour inputs leads to a smoother pattern to productivity, with the spike and then fall in productivity during COVID-19 becoming smaller. Moreover, using the annual data average growth in market services productivity is slightly slower than implied by the headline index, at around 0.2 per cent per year from 2018/19 to 2022/23, compared to around 0.6 per cent per year in the official statistics (Figure 7). This suggests that, according to this measure, growth in labour quality accounted for around two-thirds of the growth in labour productivity over the period.

Figure 7: Labour Productivity Indices



Notes: Market sector.
Sources: ABS; Authors' calculations.

Focusing on 2022/23, the slight tick down in labour quality may have subtracted around 0.4 percentage points from growth in the year. So while changes in labour quality may have contributed to some weakness in productivity recently, over the full COVID-19 period they supported productivity growth.

It is important to keep in mind that what we are focusing on here is purely a measure of the 'inherent' productivity of workers. As discussed above, we are not considering how well matched they are to a job, and this may have important implications for productivity (see Wang and Wiley *forthcoming*).

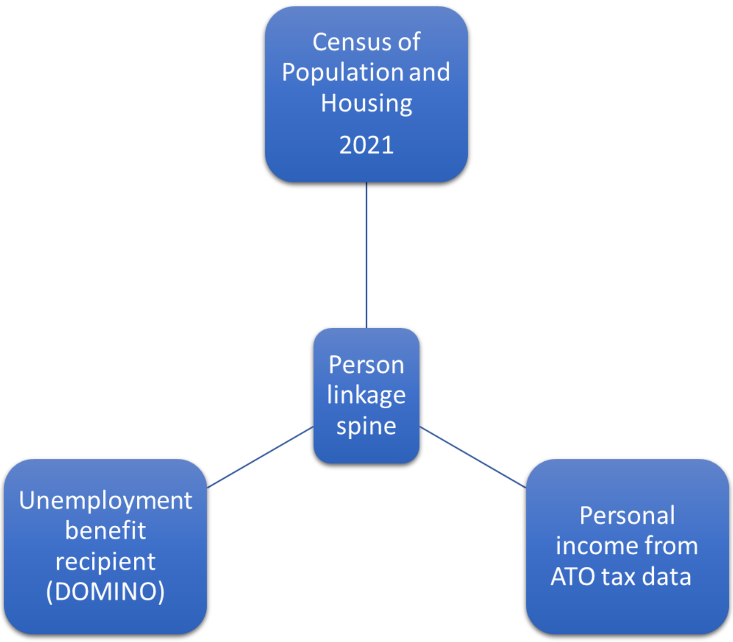
Moreover, the approach itself is very simple and subject to several caveats. For example, wages represent an imperfect proxy for productivity, so our sense of the labour quality of different groups could be wrong. And even though wages are a good proxy for productivity, there may be important factors that determine a person's human capital and productivity that are not captured in the indices, but which may be changing over recent years. We consider this in the next section.

4. Exploring the Drivers of Human Capital Using Integrated Microdata

To date, QALI indices have tended to focus on a relatively small number of observable worker characteristics, namely age (as a proxy for experience) and education. In part this reflects a preference for parsimony. But it also reflects data availability. While the Census data used to estimate wage and productivity metrics that feed into QALI indices is extremely rich, there are potentially important factors that could be associated with human capital that are not captured. For example, while age may be a good proxy for experience for most people, some people may have spent extended periods out of the labour force, for example due to caring responsibilities or unemployment spells. Capturing such information could be valuable.

The increasing availability of integrated microdata has the potential to start to capture a greater range of these important characteristics. In this section, we explore being to explore this potential. Specifically we use the fact that Census, ATO tax data, and unemployment benefit recipient data (DOMINO) have all been integrated as part of PLIDA (see Figure 8). The intent of this section is not to build an ideal model of human capital. But rather to demonstrate the value that can potentially be gained though incorporating additional information contained in these integrated datasets.

Figure 8: Data Assets



4.1 Modelling framework

We build off the existing ABS methodology to model human capital, which informs the existing official QALI index (ABS 2022). This involves modelling hourly wages reported in the Census as a function of using education and age. In doing so we control for several other factors that may affect wages, but that are not necessarily related to the 'inherent' human capital or productivity of the worker, such as gender and occupation. This is based on the standard Mincer (1974) earnings regression which has remained core to human capital models.

More specifically, we run the following regression:

$$\ln(hourly\ wage_i) = \beta_i Age_i + \beta_2 Education_i + \gamma \mathbf{X}_i + \varepsilon_i$$

Where $hourly\ wage_i$ is measured as the ratio of the reported income and hours worked, Age_i is a series of 0/1 dummy variables for 10-year age buckets, and $Education_i$ is a series of 0/1 dummy variables taking for the worker's education group.[5]

The vector $\mathbf{X}_i$ contains several controls. These include gender, industry and occupational skill level. As noted above, these are not intended to directly capture human capital. But rather to control for some other factors that may influence wages. For example, due to gender wage gaps, wages may tend to be lower for women. If women are more likely to have a Bachelor degree or higher, failing to account for gender could therefore bias our estimates of the effect of education on human capital.

We then extend the existing framework to include some additional variables constructed using the integrated microdata sets. Specifically, we consider three additional variables.

The first is spells out of employment (Spells). As noted above, age will be a reasonable proxy for experience for most workers. However, some may have spent periods outside the labour force. If this is the case, age will be an imperfect proxy for experience. And if human capital accumulated differently during these periods, or even atrophies, this could bias our estimates. There are good reasons to think that this might be the case, as there is a large literature showing that periods of unemployment can be associated with some skills atrophy and therefore lower wages (e.g. Schmieder, von Wachter and Bender 2016; Lachowska, Mas and Woodbury 2020; Cassidy *et al* 2020).

To account for this, we use the longitudinal tax data included in PLIDA from 2001-2019. We construct a measure of the number of years the worker did not report receiving either labour or business income, where the latter captures self-employed workers. We use this to create a series of 0/1 dummies for number of years out of employment (see Table 1 for groupings).[6] This will be an imperfect proxy for spells outside of the employment. For example, it will not capture spells that do not span an entire financial year. It may also capture periods where people are working

5 Hourly wages are derived from the categorical income measure divided by hours worked from the 2021 Census data. We drop observations where people work less than five hours a week and more than 70 hours per week in main job. Education groups are unskilled, skilled, bachelor and higher degree.

6 This is similar to Guvenen *et al* 2020, who include a cumulative mismatch measure in their version of a Mincer regression. The correlation between unemployment spells and cumulative unemployment is not too high.

overseas. But it can still likely provide some useful insights, and further work could refine the metric.

The second metric is periods receiving unemployment benefits (i.e. Newstart or JobSeeker) from the DOMINO data. The motivation for this variable is similar to the above, but these data can potentially better capture shorter spells outside of employment given they are reported at a higher frequency. For the purposes of this paper, we construct a variable indicating whether someone was on an unemployment benefit payment in 2018/19. Further work could extend this to consider total periods ever on payments.

The final variable we consider is a worker's tenure in their main job. The motivation for this variable is that workers tend to build up job-specific human capital over time in a job as they develop familiarity with job tasks, organisational process, and other factors. This will tend to be reflected in higher wages and productivity (e.g. Buchinsky *et al* 2010).

Accounting for the effect of job tenure could be thought about in two ways, depending on whether we want to capture in the QALI index only inherent *general* human capital, or also include *job-specific* capital. In the former case we could think about it as another control, that tries to capture a factor that drives wages but that is unrelated to inherent general human capital. Including the control could help use separate out the effects of overall work experience in building general human capital, from the effects of tenure in driving job-specific human capital.[7] Alternatively, if we want the QALI index to capture both general *and* job-specific human capital, this variable can be thought about as a variable of interest.

We construct a job tenure variable using annual de-identified Pay As You Go (PAYG) payslip data. We use these to calculate number of years each person has been employed by their main (highest paying) employer as at the 2019/20 year.[8] As with other variables, we turn tenure into a series of 0/1 dummies that capture tenure groupings (see Table 1 below). This allows for the possibility that tenure has a nonlinear effect on human capital and wages (Stole and Zwiebel 1996; Lazear 2009).

4.2 Results from human capital modelling

Focusing first on the main variables included in the existing official index, namely age and education, our results are as expected. Wages, implicitly human capital, increase with age. The trajectory is steepest early on, with 25–34 year old workers tending to earning a bit over 30 per cent more than 15–24 year old workers, and 35–44 year old workers earning a further 15 percentage points more (Table 1, Column 1). Similarly, wages increase with education. The increase is particularly sharp between those with skilled vocational training and those with a Bachelors degree.[9]

7 The distinction between general human capital and firm-specific human capital has also been explored in Becker (1964), Beaudry and DiNardo (1991) and Baker *et al* (1994).

8 We also calculate a maximum tenure variable that reflects the person's longest tenure across any job held in 2019/20. We find the two measures are strongly correlated (correlation coefficient of 0.9) and so focus on tenure in their main job. We note that tenure in 2019/20 may not align to the job reported held as at Census date. But we lag the information by a year to limit the effects of COVID-19 and related policies.

9 There is also evidence of a gender gap, with women tending to earn around 8 per cent less than men.

Table 1: Human Capital Model Results

Main results, key coefficients

	Base (1)	Add industry (2)	Add Occ Skills (3)	Tenure model (4)	Spell model (5)	Benefit model (6)
Age						
24–34	0.319***	0.284***	0.251***	0.197***	0.188***	0.254***
35–44	0.467***	0.420***	0.369***	0.310***	0.312***	0.372***
45–54	0.488***	0.439***	0.385***	0.318***	0.330***	0.388***
55–64	0.469***	0.424***	0.376***	0.302***	0.320***	0.379***
65+	0.540***	0.510***	0.450***	0.383***	0.406***	0.452***
Education						
Skilled	0.132***	0.104***	0.059***	0.096***	0.079***	0.096***
Bachelor degree	0.354***	0.293***	0.142***	0.185***	0.167***	0.184***
Higher Degree	0.426***	0.359***	0.192***	0.228***	0.213***	0.227***
Unemployment Benefit						–0.099***
Spell						
1–2 years					–0.017***	
3–5 years					–0.048***	
6–8 years					–0.072***	
9+ years					–0.094***	
Tenure						
1–2 years				0.026***		
3–5 years				0.049***		
5–10 years				0.076***		
10–15 years				0.098***		
15–20 years				0.129***		
20+ years				0.154***		
Female	–0.081***	–0.088***	–0.078***	–0.083***	–0.079***	–0.077***
Industry controls	N	Y	Y	Y	Y	Y
Occupation skill level controls	N	N	Y	Y	Y	Y
R^2	0.181	0.224	0.266	0.266	0.284	0.231
Observations	10,572,225	9,616,710	9,534,058	9,534,058	7,872,511	8,440,593

Note: ***, ** and * denote statistical significance at the 1, 5 and 10 per cent levels, respectively. Standard errors robust to heteroskedasticity.

These results are reasonably robust to the inclusion of additional controls, such as controls for industry (Column 2) and occupational skill level (Column 3). That said, adding occupational skill level substantially lower the effects of education. This provides some evidence that the role of education may be slightly overstated in the standard approach, and we may be capturing the fact that higher educated workers tend to sort into higher paying jobs. Whether or not we want to capture such effects in a QALI index is an open question.

Turning to our additional variables, consistent with the literature we find that wages tend to rise with job tenure, with the increases tending to be sharper for lower tenure workers. Including this variable lessens the role of age somewhat, suggesting that part of what we tend to identify as the effects of age and experience on general human capital may actually be the accumulation of job-specific human capital via tenure. As such, if the index is meant to capture only the former, it may be overstating the role of age.

Interestingly, if we interact tenure with gender or age, we find that the returns to job tenure are lower for women and for older people.[10] The latter findings suggests that accumulation of job-specific capital may be more important for young workers, and less important for older workers. This is not entirely surprising, as older workers may be more likely to start new jobs more aligned with their experience, whereas younger workers may be more likely to change careers and fields. This may be important distinction to make in trying to separately assess the role of general and job-specific human capital.

Focusing on the Unemployment Benefit and Spells variables, we do see significant effects. Workers that spent some time on benefits tended to have wages that were around 10 per cent lower than other workers. Similarly, those with spells outside of employment also had significantly lower wages.

Again, exploring the heterogeneity of these effects shows some interesting results. We find that the wage penalty for spells out of employment are smaller for women and for older workers. Given women may be more likely to spend time outside of the labour force for caregiving, the former may indicate a difference between years spent out voluntarily for caregiving, versus involuntarily due to job loss. Further work can explore this in more detail.[11]

4.3 How have these additional dimensions changed over time?

The above indicates that various factors not included in in the official, or our higher frequency index could affect human capital and labour quality. A key question then is, has the share of workers with these characteristics changed substantially over recent years, and therefore could our understanding of labour quality based on the previous indices be misleading?

To explore this we use two sources of data. To explore job tenures, we again use LLFS data. This contains information on tenure in current main job, and so is well suited to understanding changes in tenure. Again we focus on the market sector to be more consistent with the scope of the ABS QALI index.

Our second data source is STP. This is a high-frequency dataset of de-identified employee payslips. As these data are integrated into PLIDA, we can consider whether there have been changes in the share of workers with spells outside of the labour market or time on unemployment benefits, using the same definitions as above.

More precisely, we take a random sample around five per cent of workers in the STP dataset. We calculate their monthly pay, and then track the share of pay accruing to different groups over time

10 Results available on request.

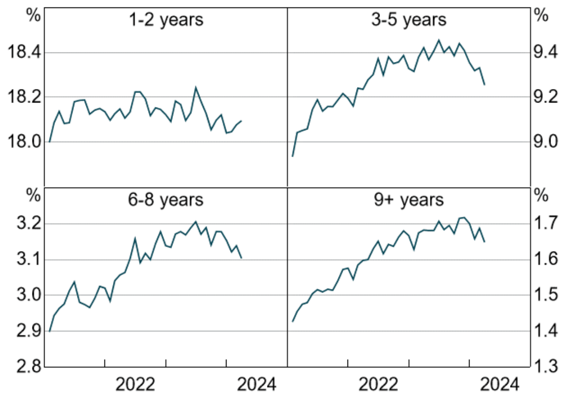
11 We considered including number of children in the regression. We find that that having children can be associated with higher or lower wage outcomes, and the size and direction of the effect is heavily dependent on gender, age (signalling cohort) and education. Results available on request.

from January 2021 to March 2024. This allows us to understand whether the share of hours worked by workers we these characteristics changed substantially over the past few years.[12]

Focusing first on spells outside of employment, we find that the share of monthly income for those who have not had an unemployment spell has fallen approximately 0.7 percentage points between late 2021 and mid-2023 (Figure 9). Conversely, the share of monthly income for those who have had an extended employment break (at least three years) has increased by around the same amount. Given the above finding that such workers tend to receive lower wages, suggesting lower human capital, this suggests that this compositional shift may have lowered the 'quality' of labour inputs. Failing to account for this may overstate the QALI index. However, given the shift is relatively small, the extent of the bias is likely very small.

Figure 9: Share of Employment Income by Spells out of Employment

High-frequency STP data



Note: 5 per cent sample of population.
Sources: ABS; Authors' calculations

We see a very similar pattern for those previously receiving unemployment benefits. The share of monthly income for those who have received benefit payments (in 2018/19) increased by 0.2 percentage points during the same period (Figure 10). Again, this may suggest labour quality has fallen slightly more than indicated by standard indices. However, the magnitude is likely to be small.

12 The lack of hours data in STP is a key weakness here. The integration of the LLFS into PIDA and the STP data would help to fix this issue.

Figure 10: Share of Employment Income by Unemployment Benefit Recipients
High-frequency STP data

Note: 5 per cent sample of population; Benefit recipient status in 2018/19.
Sources: ABS; Authors' calculations.

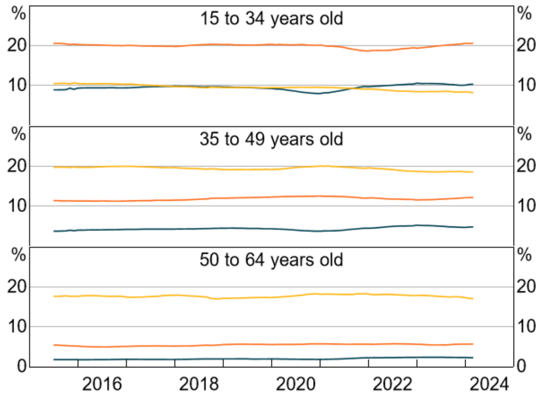
Interestingly, since mid-to-late 2023, the share of income accruing to both groups has fallen slightly. This has occurred alongside a general softening in labour markets. Further data will be needed to assess whether this pattern continues.

One point to highlight with the above analysis is that due to the lack of hours data in STP we have not been able to separate hours from wages, which would allows us to better align with existing QALI index construction approaches. The integration of the LLFS with PIDA could address this issue. More generally, it would allow us to incorporate some of these characteristics into the LLFS data, increasing the richness of the LLFS data.

Turning to tenure, we do see some increases in the share of workers with less than one-year in a job (Figure 11). This is evident across all age groups. Again this may suggest standard QALI indices are slightly overstating the quality of labour inputs (if we take the board view of trying top capture general and job-specific human capital). However once again the changes are relatively small. Moreover, other work using HILDA suggests that self-assessed measure of job-match have not moved substantially, suggesting the effects of the increased job mobility on productivity may be relatively small (Wang and Wiley forthcoming).

Figure 11: Share of Hours Worked in All Job

By job tenure and age, 12-month moving average



Sources: ABS; Authors' calculations

5. Conclusion

Understanding current and future developments in productivity is crucial for policymakers. The increasing availability of high-quality, integrated microdata sources significantly increases the potential to measure one key driver of productivity, human capital and labour quality, in a more timely and rigorous manner.

This paper has taken some first steps towards such measurement. In doing so we have shown that, at least based on standard metrics, human capital in the labour force increased over the COVID-19 period, rather than declined as some have argued. This would have contributed to productivity growth, rather than subtracted.

That said, we also show that there are potentially many aspects of human capital that are not captured by current approaches, but which may be able to be incorporated due to the increasing availability of integrated microdata sets. This highlights the potential value of such data projects and sources for statistical and research purposes, including measuring human capital. Future integration of projects, such as the integration of the LLFS to PLIDA, will only increase this value.

References

ABS (Australian Bureau of Statistics) (2005), *Quality-adjusted Labour inputs, Research Paper, cat. no. 1351.0.55.010.* Retrieved from <https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1351.0.55.010Nov%202005?OpenDocument>.

ABS (2021), *Australian System of National Accounts: Concepts, Sources and Methods*, Retrieved from <https://www.abs.gov.au/articles/understanding-labour-quality-and-its-contribution-productivity-measurement>.

ABS (2022), Understanding Labour Quality and Its Contribution to Productivity Measurement*.* Retrieved from <https://www.abs.gov.au/articles/understanding-labour-quality-and-its-contribution-productivity-measurement>.

Australian Treasury (2023), *Intergenerational Report,* Retrieved from <https://treasury.gov.au/sites/default/files/2023-08/p2023-435150.pdf>.

Baker G, M Gibbs and B Holmstrom (1994), 'The Internal Economics of the Firm: Evidence from Personnel Data', *The Quarterly Journal of Economics*, 109(4), pp. 881–919.

Beaudry P and J DiNardo (1991), 'The Effect of Implicit Contracts on the Movement of Wages Over the Business Cycle: Evidence from Micro Data', *Journal of Political Economy*, 99(4), pp.665–688.

Becker GS (1964), Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education. 3rd ed. The University of Chicago Press, Chicago.

Brown A and R Guttman (2017), 'Ageing and Labour Supply in Advanced Economies', *RBA Bulletin*, December, pp 37–46.

Bruno A, J Dunphy, and F Georgiakakis (2023) 'Recent Trends in Australian Productivity', *RBA Bulletin*, September, pp 1–9.

Buchinsky M, D Fougere, F Framarz and R Tchernis (2010), 'Interfirm Mobility, Wages and the Returns to Seniority and Experience in the United States', *The Review of Economic Studies,* 77(3), pp. 972–1001.

Cassidy N, I Chan, A Gao and G Penrose (2020), 'Long-term Unemployment in Australia', RBA Bulletin, December, pp 45-56.

D'Arcy P and L Gustafsson (2012), 'Australia's Productivity Performance and Real Incomes', *RBA Bulletin*, June, pp 23-35.

Duretto Z, O Majeed and J Hambur (2022), 'Overview: Understanding Productivity in Australia and the Global Slowdown', Treasury Round Up, October, p4–13.

Guvenen F, B Kuruscu, S Tanaka and D Wiczer (2020), 'Multidimensional Skill Mismatch', *American Economic Journal: Macroeconomics*, 12(1), 210–244.

Lachowska M, A Mas and SA Woodbury (2020), 'Sources of Displaced Workers' Long-term Earnings Losses', *American Economic Review*, 110(10), pp 3231–3266.

Lazear E (2009), 'Firm-specific Human Capital: A Skill-weights Approach', *Journal of Political Economy,* 117(5), pp 914–940.

Mincer J (1974), *Schooling, Experience, and Earnings*, National Bureau of Economic Research, Cambridge. Retrieved from <https://www.nber.org/books-and-chapters/schooling-experience-and-earnings>.

Productivity Commission (2023), 'Quarterly Productivity Bulletin December 2023', PC Productivity Insights, December.

Schmeider JF, T von Wachter and S Bender (2016), 'The Effect of Unemployment Benefits on Nonemployment Durations and Wages', *American Economic Review*, 106(3), pp 739–777.

Stole L and J Zwiebel (1996), 'Intra-firm Bargaining under Non-binding Contracts', *The Review of Economic Studies,* 63(3), pp 375–410.

Wang L and G Wiley (Forthcoming), 'Skills Match Quality following Covid-19', *RBA Bulletin*, Forthcoming

Copyright and Disclaimer Notice

BLADE Disclaimer