Using new data sources to understand and monitor changes in prices, wages and incomes

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Abstract

New, timely and detailed administrative and other micro-datasets are opening new ways for policymakers to understand and monitor changes in prices, wages and incomes, to better inform real-time policy decisions. This paper gives an overview of some of the ways that the Reserve Bank of Australia has been using these new datasets, such as in the construction of new and timely measures of labour income, and measures of broader household income for different demographic groups. It also discusses early insights from a recently linked dataset made up of firm administrative data and web-scraped consumer prices data for a selection of large retailers. Preliminary findings suggest that in 2022: the distribution of price changes rose; prices that have typically been stickier started to change more frequently; and the overall frequency of price changes increased. Initial analysis also suggests that the price data could be valuable in understanding the pass-through of cost shocks to firm's final prices. While all the datasets discussed in this paper already have scope to provide tremendous value to policymakers, further work to link and supplement them with other administrative and private-sector datasets would significantly enhance their value.

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1. Introduction

In recent years, the Australian Bureau of Statistics (ABS) and Australian Tax Office (ATO) have released a variety of powerful integrated administrative and related datasets to Government and researchers, placing Australia at the global frontier of data availability (Gruen 2022). This has significantly increased the scope for evidence-based policymaking and underpinned responses to recent major policy challenges. For example, the availability of integrated high-frequency employment and social services data helped guide the Government's response to the COVID-19 pandemic (Hambur *et al* 2022; Kennedy 2022; Australian Treasury 2021; Shergold *et al* 2021). These data have also provided critical insights into other policy questions such as slowing productivity (Andrews and Hansell 2021; Andrews *et al* 2022; Hambur 2023) and increased scope to assess the efficacy of public policies (e.g. Win, Hambur and Breunig forthcoming; Sainsbury, Breunig and Watson 2022; Herault, Vu and Wilkins 2020).

To date much of the focus of analysis using the new datasets has been about 'real' economic outcomes, such as employment, productivity, and business investment. This is not surprising given both the economic importance of real outcomes and the nature of administrative datasets, which often lack information on nominal prices. Still, nominal outcomes and questions are vital for economic management, as highlighted by the recent sharp increase in inflation in Australia and across the world. Questions around the extent and speed of pass-through of cost shocks to prices and wages have obvious policy implications for an inflation targeting central bank. Questions around the extent and distribution of income growth have implications for Government tax revenue, and for households' spending power and wellbeing. And questions around cost pass-through to prices and profits are important for competition authorities. Given this, the increased availability of datasets that help us better to understand nominal variables is crucial, particularly if they are available with a short lag.

The availability of several new integrated datasets represents an important step forward. These include the integrated high-frequency employment and social services data mentioned above, as well as microdata underlying the ABS Wage Price Index (WPI) and web-scraped consumer prices data that have been integrated with data on firm characteristics and financial variables. These datasets open a path to answering important policy questions that will facilitate a greater understanding of the outlook for wages, incomes, and prices, as well as their drivers and facilitate better policymaking. such questions include: how is income inequality developing in real-time and what are the implications for household consumption? What share of household income growth is driven by people moving to new jobs, and is this sustainable? And is there evidence that firms are changing their prices more frequently, or passing on more input costs to consumers over time?

Against this backdrop, this paper provides an overview of some of the ways that the Reserve Bank of Australia (RBA) is using these datasets to monitor developments in nominal variables, and to explore long- and short-run policy questions. It also discusses future directions for data availability that could provide significant additional value, including making other data sources publicly available and linking currently available datasets together.

2. A brief overview of the data landscape

This paper primarily focuses on two administrative datasets:[1]

- The Business Longitudinal Analysis Data Environment (BLADE): a business-level dataset containing anonymised administrative tax fillings for the near universe of Australian firms. The data are integrated with several ABS surveys and other administrative data such as firm patents and trade data.

- The Multi-agency Data Integration Project (MADIP): a person-level dataset containing anonymised integrated tax, social services and other administrative and survey data for the near universe of Australian residents. The data are also integrated with high-frequency employment data collected as part of the ATO Single Touch Payroll (STP) reporting system, which comprises payment summary information is reported to the ATO each time a worker is paid.

Both datasets have been available for several years. But over the past couple of years they have become richer as new survey and administrative datasets have been integrated, updates have become more frequent and access for policy and research has been widened (Gruen 2022). The two have also been linked together, facilitating analysis that integrates information about firms and individuals.

3. Better understanding wage outcomes

Having a good understanding of wages growth is important for policymakers. For central banks, wages growth is a key determinant of inflation, reflecting the fact that wages are a key input cost for businesses. Strong wages growth may reflect a healthy labour market, but it can also point to de-anchoring of inflation expectations and rising risk of price-wage spirals (e.g. Lowe 2022; Alvarez *et al* 2022; Boissay *et al* 2022). Wages growth is also a key component of government tax revenue and key determinant of household income and welfare.

The increased availability of micro-datasets creates opportunities to gain deeper insights into wages growth, supplementing more aggregated data sources such as the WPI and Average Earning in the National Accounts (AENA) in Australia. For example, microdata can be used to draw out information on the structural drivers of wage growth (Hambur 2023b); and they can also be used to construct new, bespoke wages growth measures to support timely monitoring of the economy and explore emerging issues.

One example of the latter from overseas is the Federal Reserve Bank of Atlanta's Wage Growth Tracker (Federal Reserve Bank of Atlanta 2023). Drawing on microdata from the Bureau of Labour Statistics Current Population Survey, the tracker provides timely and detailed information on wages growth cut by workers' demographic and job characteristics. This provides useful insights into the

1 A third major administrative dataset is the ATO's ALIFE (ATO Longitudinal Individuals File). This contains anonymised individual-level tax return data. It has a richer set of taxation-related variables and a longer longitudinal sample than MADIP, which makes it more suitable for studying long time horizons and for policy questions focused on taxation. Compared to MADIP, ALIFE has less information on other aspects of individuals.

nature of wages growth, including whether it is widespread or driven by specific sub-groups, such as the low wage earners. These insights facilitate a better understanding of the strength of the labour market at any given point and support better wages forecasts.

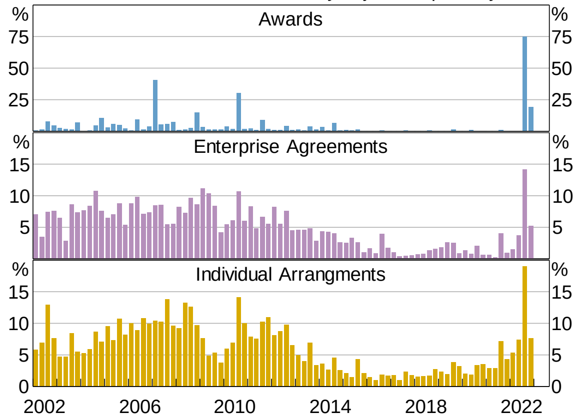
Similarly, the Reserve Bank of New Zealand (RBNZ) recently included a chapter in their Monetary Policy Statement drawing on high-frequency administrative payment summary data to do a deep dive into wage and labour market outcomes (RBNZ 2023). The chapter explored the role of job-switching in wages growth post COVID-19, as well as extensive and intensive margins of wage growth (i.e. how frequently people's pay increased versus the size of the increase). The RBNZ used this information to conclude that wage inflation was likely to remain high in coming months.

3.1 WPI

The RBA has completed a significant work program over the past 5-10 years using WPI microdata to construct new analytical series for use in monitoring and forecasting. Much of this work is summarised in Bishop (2016) and Bishop and Cassidy (2019), which examine the size and frequency of wage changes and wage growth by pay-setting mechanism, respectively.

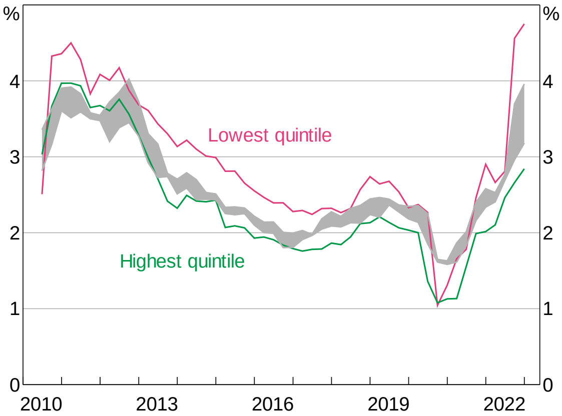
This additional information has been extremely valuable, particularly in the recent period of elevated price inflation. For example, the data have been used to document the breadth of wage increases, with a growing share of workers receiving wages growth above 4 per cent (Graph 1). The data also highlight the important role of changes in award and minimum wages in overall wage dynamics, in terms of their contribution to the increased share of large wage increases and wage increases being relatively stronger for low wage earners, a subject we return to below (Graph 2).

Graph 1
Wage Changes Above 4 Per Cent*
Private sector, non-seasonally adjusted, quarterly



* As a share of all jobs by method of setting pay.
Sources: ABS; RBA

Graph 2
Wages Growth by Hourly Wage Quintile*
Year-ended



* Grey range denotes wages growth for hourly wage quintiles 2–4.
Sources: ABS; RBA

More recently, WPI microdata have been linked to firm-level tax and survey data (BLADE) for a one-off project to facilitate more in-depth research. While this work is in its early stages, it creates the potential to allow other dimensions of wage growth to be explored, such as growth by firms' size, growth trajectory, innovation status, profitability and trade activity. The data can also be used to characterise the relationship between wages and firm outcomes such as profitability and prices (see below). Leveraging the existing integration between MADIP and BLADE, the WPI microdata could also provide scope to bring together demographic information about the workers at a given firm, such as their work history and education, with information on their hourly wages, facilitating a better understanding of the role of worker characteristics in wage determination.

3.2 STP

As noted above, the ATO's STP database consists of payslip information reported to the tax office each time a worker is paid. The frequency and timeliness of these data, along with the breadth of coverage across the workforce and different types of pay (regular, overtime, bonus, superannuation etc.) make STP an extremely valuable source of real-time information on labour income, with unique benefits compared to other data sources.

For example, Average Earnings National Accounts (AENA) provides a very comprehensive measure of labour income. However, AENA tends to also be very volatile, and heavily affected by compositional changes in the labour force, particularly in recent years due to COVID-19, which can obscure underlying signals about labour market strength. Additionally, it is also only available on a quarterly basis with a lag of several months.

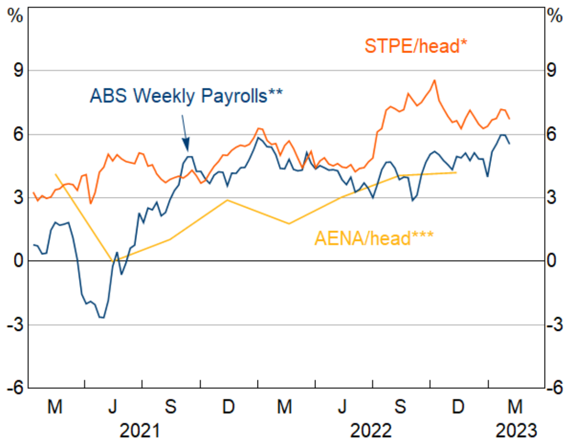
In order to address some of these limitations in AENA, the RBA has recently developed a set of compositionally-adjusted STP-based measures of earnings growth. These provide a higher frequency and lower volatility read on the evolution of labour income across the economy.[2] This is achieved by tracking wage changes within worker-firm relationships over time, which abstracts from many compositional changes in the labour market that drive volatility in AENA. The

2 This work was developed internally by RBA economists James Bishop and Nalini Agarwal.

granularity of the STP data also allows us to remove the impacts of government programs such as JobKeeper, which are included in published broad measures of labour income and obscure information about how the balance of labour market supply and demand translates to changes in pay.

Graph 3 compares the RBA's compositionally adjusted measure of STP earnings per job ('STPE/head') to the ABS's AENA per head measure, as well as an unadjusted STP-based measure that simply divides the ABS Weekly Payroll Jobs series by the Weekly Payroll Wages series. Both AENA and the ABS unadjusted STP measure display a sharp decline in labour income growth in mid-2021. This primarily reflects a compositional shift in the labour force, as many lower paid workers returned to the labour force after having previously exited during June quarter 2020 when the Australian economy entered lockdowns. In contrast, the compositionally-adjusted STP measure smooths through this period by tracking stable firm-worker relationships, producing a series with behaviour more aligned with the (conceptually similar) WPI. Growth in the adjusted STP measure has recently increased relative to the unadjusted measures.

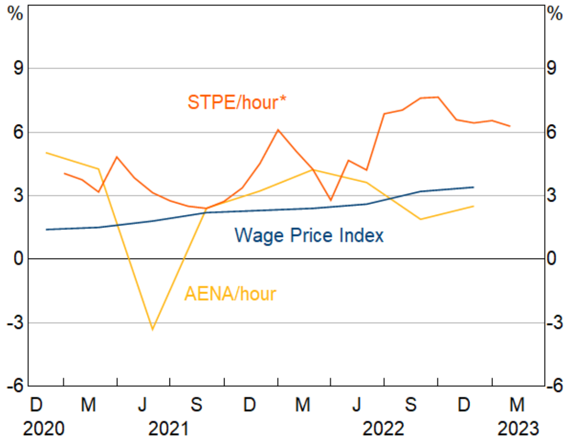
Graph 3
Average Earnings Per Job Growth
Year-ended



* Weekly earnings per job using compositionally adjusted ATO Single Touch Payroll microdata; non-farm.
** Combination of Total Wages and Payroll Jobs indices from ABS Weekly Payroll Jobs and Wages in Australia; all industries.
*** Non-farm.
Sources: ABS; ATO; RBA

One weakness of the STP data is that it has no measure of hours. This limits the ability to construct measures of earnings per hour, which may be more relevant for thinking about wages growth. To get around this limitation, the RBA has recently constructed an experimental hours measure on a comparable basis from the microdata underlying the Labour Force Survey (L-LFS). This has been combined with STPE/head to create a timely, monthly frequency, compositionally-adjusted STP earnings per hour measure ('STPE/hour') to supplement AENA per hour. As with STPE/head, the initial results suggest that STPE/hour is less volatile than AENA per hour, reflecting the fact that it removes many of the short-term compositional labour market shifts that make quarterly AENA/hour difficult to interpret (Graph 4). Relative to STPE/head, growth in STPE/hour has been slightly weaker in recent months, in line with a recent pickup in average hours worked.

Graph 4
Hourly Wages Growth
Year-ended; non-farm



* Weekly earnings per job from ATO Single Touch Payroll data, deflated by hours worked from the ABS Labour Force Survey; compositionally adjusted.

Sources: ABS; RBA

The availability of STP data has already provided valuable insights into wages growth. And its value is only likely to grow as the sample becomes longer, and as STP Phase 2 is introduced, which will provide additional information on leave and other aspects of pay (ATO 2023).

In terms of future directions though, one potentially very valuable direction would be to explore the feasibility of merging STP (and MADIP more generally) with the L-LFS, as has been done in New Zealand for their equivalent datasets (Zabala *et al* 2012). If there is sufficient identifying information to do this (even imperfectly), the integration would bring measures of hours worked directly into STP that could be used to make more robust hourly labour income growth measures. When combined with leave data from STP Phase 2, the integration would also provide valuable information on the role of paid versus unpaid leave in variation in working hours, and thereby improve our understanding of seasonal dynamics in aggregate labour income.

4. Understanding income and heterogeneity

There is a growing understanding that household heterogeneity in outcomes and characteristics can be important for answering macroeconomic questions. The presence of constrained (or potentially constrained) households and idiosyncratic risk can change the transmission of shocks and economic policy throughout the economy (Acharya and Dogra 2020; Branch and McGough 2020). For example, if a large share of consumers is credit-constrained, they may be less able to smooth consumption when faced with negative shocks to their income, leading to larger economic swings in the aggregate. And inequality has become a topic of increasing interest, both for its own sake (Piketty, Saez and Zucman 2018), as well as due to its potential implications for economic growth, savings and interest rates (e.g. Mian, Staub and Sufi 2021; Breunig and Majeed 2020).

Understanding outcomes for different households' income in real-time can therefore be extremely valuable to policymakers. It can help them assess how conditions are shaping inequality in a general sense. And it can provide useful insights on whether certain segments of the population are likely to become constrained and pull back significantly on spending.

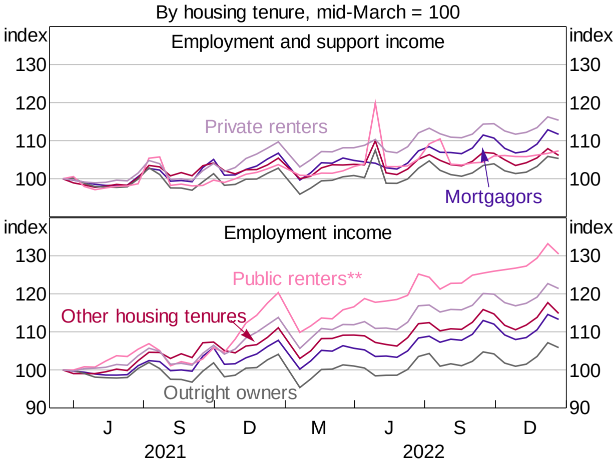
To date, timely information on income across the distribution and real-time inequality has been limited. That said, Blanchet, Saez and Zucman (2022) outline a new estimate of real-time income inequality drawn together from several sources, including the Current Population Survey data discussed above. Similarly, Larrimore, Mortenson and Splinter (2023) explore income changes across the distribution during COVID-19 using administrative data.

4.1 STP/DOMINO

Similar to Blanchet, Saez and Zucman (2022) and Larrimore, Mortenson and Splinter (2023), staff at Treasury and the RBA have been using recently integrated high-frequency STP employment data and social services payment DOMINO data from MADIP to model and monitor income growth for different groups. When combined, these provide information on two of the largest components of household income.

For example, Agarwal, Gao and Garner (2023) use these data, combined with Census microdata, to examine outcomes for renters versus homeowners. They find that renters' wage and support income has tended to grow more quickly than homeowners on average over the past two years, which could help to alleviate some of the pressures from rising rents (though affordability will still likely have worsened for some renters). Graph 5 updates this analysis and shows that the gap between income for renters and other housing tenure groups has remained persistent. Patterns are similar if these data are constructed on a per person or per job basis.[3]

Graph 5
Employment and Support Income*
By housing tenure, mid-March = 100



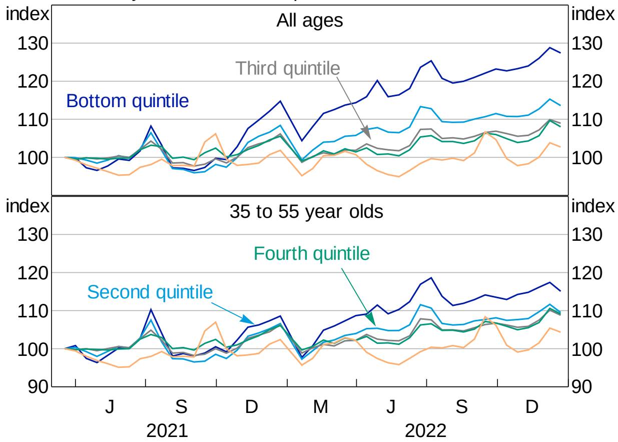
* Includes STP employment income and income support payments. Excludes COVID disaster support payments, which lower support incomes in September to November 2021 Individuals assigned housing tenure status based on 2021 Census data.
** Includes renters in public or social housing.
Sources: Integrated STP and DSS data.; RBA

Similarly, Australian Treasury (2021) found that employment and support income growth was strongest in 2020 for individuals who were in the lowest income quintile in the previous year (focusing on those filing tax returns the previous year). In large part, this reflected JobKeeper and income support payments. Graph 6 updates this analysis, focusing on the more recent period.

3 Due to data issues COVID disaster payments are removed from this analysis, so income from around September to November 2021 will be slightly understated.

Similar trends are evident, with employment and support income growing most strongly amongst those in the lowest income quintile (based on their previous year's income). Similar patterns are evident if we focus on per person or per job metrics, which helps to abstract from people entering or exiting the sample (e.g. due to losing eligibility for support payments). These findings are consistent with strong labour markets, as well as strong wages growth for lower skilled and lower income workers based on WPI data (as discussed above).

Graph 6
Employment and Support Income*
By 2019/20 income quintile, mid-March = 100

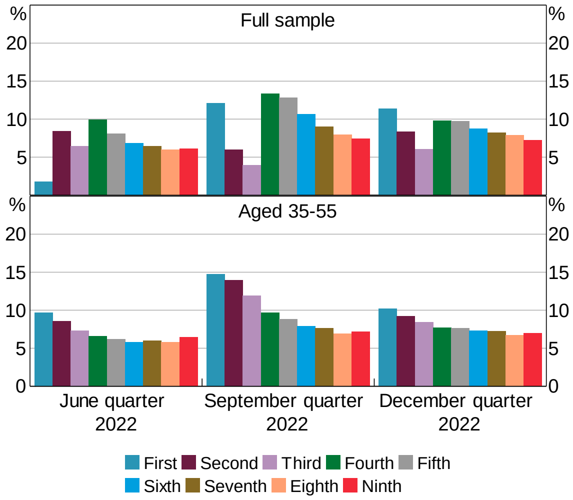


* Includes STP employment income and income support payments. Individuals assigned income quintile based on 2019/20 tax data. Excludes COVID disaster payments, so income understated around September to November 2021.

Sources: Integrated STP and DSS data.; RBA

These findings are robust to other ways of measuring outcomes. For example, redefining the distribution in each period - rather than fixing groups at the start of the period - leads to a smaller outperformance for lower income individuals but does not change the story. Similarly, including individuals without an income history does not change the results in terms of employment income. However it does change the story when focusing on employment and support income, with income growth being strongest for individuals on low-to-middle incomes, rather than low incomes. This reflects the fact that in this case many of those in the lowest income group receive only support payments, which have grown at the indexation rate (Graph 7).

Graph 7
Employment and Support Income Growth Across the Distribution
Quarter average on quarter average growth rate, by decile



* Orders workers by employment and support income in each fortnight, calculates percentiles, and contruct growth rates. Includes all employed or support payment earning people. Data on disaster payments excluded, which may overstate growth in September and December quarters.

Sources: ABS; Integrated STP and DSS data; RBA

While these measures of income growth across different groups have already proved valuable, they can still be improved. Conceptual issues remain around how best to construct measures of growth across the distribution, as discussed above. And more years of data will provide a better sense of what patterns look like in normal times: for example, how much of the faster growth in incomes for renters reflects the fact that they tend to be younger?

Moreover, while labour and support income are two large components of household income, other income sources such as business and capital income are still important, particularly for some groups. The integration of BLADE to MADIP coupled with new data on business ownership could provide a source of business income data. But other data or modelling techniques may be required to assess capital income.

The other missing piece is information on consumption. With this information policymakers could have a clearer understanding of the effects of income changes on individuals' behaviour and the economy. Private sector sources, such as banking and credit data, represent a potentially extremely valuable source for such information. While the scope to integrate this private sector data into administrative data may be limited, they could still play a crucial role in helping policymakers to close the loop and better understand and monitor the link between consumption and household income.

5. Examining price formation and its determinants

The recent sharp and unexpected rise in global inflation has highlighted the need for central banks and other policy institutions to improve their understanding of price-setting dynamics (Gopinath 2022; BIS 2022). Disaggregated prices data and microdata can play an important role in this regard, allowing researchers to drill down to item, firm and other levels to construct bespoke measures that more accurately model the diverse drivers of price behaviour and pricing decisions.

The availability of prices microdata from sources such as retail scanning, web-scraping and the release of data underlying the Consumer Price Index (CPI) has increased markedly overseas over the past two decades (Cavallo 2018). These data have been used by policymakers and academics to explore several important questions, including how ‘sticky’ certain prices are (i.e. how frequently they tend to change), which is an important determinant of the effectiveness of monetary policy, as well as to which prices central banks should pay more attention (Cavallo 2018; Eusepi, Hobjin and Tambalotti 2011). Such data have also been used to improve CPI forecasts (Aparicio and Bertolotto 2020) and better understand and monitor price developments during economic shocks (Davies 2021).

Other authors have exploited the power of linking prices data to other microdata sets, such as firm data. For example, several recent papers have used producer price index (PPI) microdata and microaggregates to look at the pass-through of shocks to firms’ costs and whether pass-through differs based on the amount of competition in the economy (Bräuning, Fillat and Joaquim 2022), or pre- and post-COVID (Amiti, Heise, Karahan and Sahin 2022). Using firm-level prices data and information on imports, exports and labour costs, papers have also explored how prices respond to input cost shocks and how this differs based on firm characteristics (Amiti, Itskhoki and Konings 2019).

5.1 Web-scraped prices microdata

Recently, the ABS has linked web-scraped prices microdata to BLADE. These data provide item-level prices at a high-frequency for 58 firms covering the period 2016 to 2022 and around 25 million unique items (though coverage is lower earlier in the sample). As well as data on the ‘advertised price’ offered to customers, from mid-2020 the data also includes the undiscounted ‘full retail price’ (or ‘full price’), allowing us to distinguish between full and sales prices (Table 1). To estimate full and sale prices prior to the start of the full price series, we use an algorithm to identify V-shaped discounts (i.e. where a price is lowered temporarily before returning to its previous level). Data are not currently available on what each product at the firm is, though work is ongoing at the ABS to make this information available.

Table 1: Prices data description

	Advertised price	Full price (raw)
Unique items (thousands)	25,081	9,155
Unique observations (millions)	366	202
Unique retailers	58	58
Absolute size of price changes[(a)]		
Mean	29	17
25th percentile	14	3
Median	22	7
75th percentile	36	21
Frequency of price changes (thousands)[(b)]	16,241	4,081

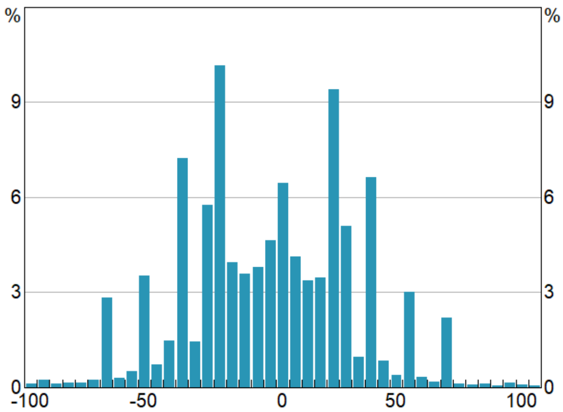
(a) Unweighted.
(b) From May 2021 onward.
Sources: ABS; RBA

Overall, the web-scraped prices microdata appear to be of a high quality and to exhibit behaviour in line with findings from similar overseas datasets (e.g. as described in Cavallo 2018). For example, changes in full prices account for only around ¼ of all price changes, indicating that a very large share of identified price changes are sales (Table 1). The absolute size of these advertised price changes is also highly dispersed, with peaks around round numbers like 25 per cent (Graph 8; Table 1). In contrast, changes in full prices are smaller (in absolute terms).

Graph 8

Distribution of Advertised Price Changes by Size*

2016-2022



* Unweighted.

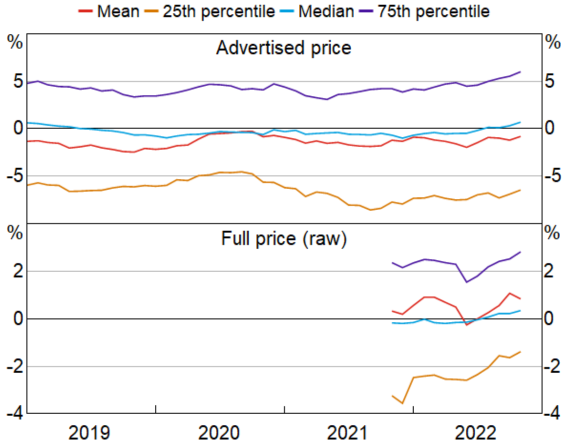
Sources: ABS; RBA

As noted above, a key benefit of the prices microdata is that they can be used to gain deeper insights into current conditions and inflation. For example, Graph 9 shows the distribution of firm-level average price changes over time. To construct this measure, we calculate the average price charged by a firm for a given item in each month. We then calculate the change for each item and take an unweighted average for each firm. This approach does not account for the importance of each item to the firm's total sales, though we do weight each firm based on their product category's weight in the CPI basket.[4]

Initial results show that over 2021, the 25th percentile of the distribution of changes for advertised prices declined somewhat, indicating that more firms were experiencing large average price declines. Over 2022, this reversed and the distribution of price changes shifted up a bit, consistent with stronger inflation. This is also evident for full prices, which are less impacted by sales-induced volatility, though the shorter sample makes interpretation more difficult.

4 If firms consistently lower the price of a good before removing it from stock, this could bias our measure downward.

Graph 9
Size of Price Changes*



* Twelve month trailing average; firm weighted, where firm weights are matched to CPI weights based on retailer type.

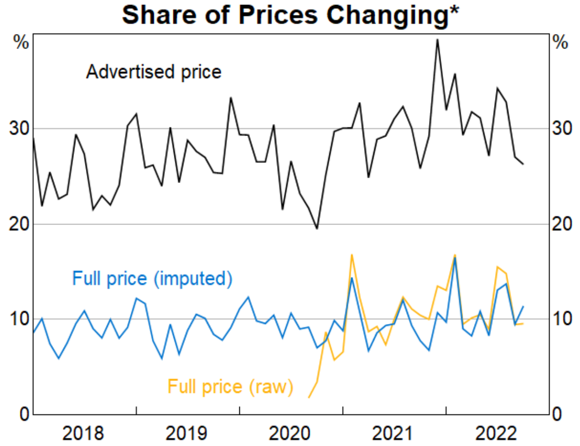
Sources: ABS; RBA

There is some evidence of an increase in the frequency of price changes for firms, as measured by the share of prices changing for the average firm (Graph 10). This is the case for both advertised and full prices. The amount of time between price changes (the 'duration') has changed somewhat as well.[5] The whole distribution of duration declined slightly around 2020 at the start of the pandemic (Graph 11). More recently the upper end of the distribution has increased. This is even more evident when we on focus on firm-level averages. Further work is needed to understand the dynamics and the potential role of compositional changes in these outcomes. However, one potential explanation for the recent pick up in duration at the upper end could be that price changes have become more common for goods that tend to be sticky and have irregular price changes.[6] This would be consistent with other work that finds that periods of high inflation can make typically persistent prices less sticky (Hall 2023).

5 Where we define duration by taking the average across items of the number of days since items last observed a price change, conditional on a price changing having occurred.

6 A similar pattern is evident if we look at the average duration across firms.

Graph 10
Share of Prices Changing*

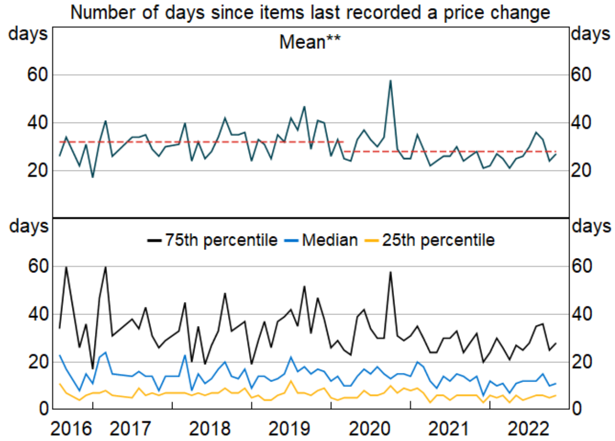


* Firm weighted, where firm weights are matched to CPI weights based on retailer type.

Sources: ABS; RBA

Graph 11
Advertised Price Duration*

Number of days since items last recorded a price change



* Unweighted.

** Dashed lines indicate mean before and after the start of the COVID-19 pandemic.

Sources: ABS; RBA

The linkage of the prices microdata to firm tax data in BLADE also allows us to gain greater insights into the drivers of price changes. For example, one question that has received a lot of attention over the past year is whether firms are passing on increases in their costs more than one-for-one to consumers, which would mean that increases in profits margins are contributing to inflation. As a very simple and initial test of this argument, we construct a measure of firm-level average price changes at a quarterly frequency (as described above) and regress these on changes in firms' gross operating margins taken from their Business Activity Statements.

Focusing on the full period since 2018 (Table 2, Column 1), we find a negative and significant association between price changes and gross margins. That is, rising prices tend to be associated with lower margins. This is consistent with other evidence that firms tend to only partly pass-through changes in their costs to final prices, reflecting competitive pressures and price stickiness (Amiti, Itskhoki and Konings 2019). There is some very tentative evidence that this relationship has become less negative over time, though not positive. This suggests that pass-through of cost shocks to final prices may have become more complete, though it still appears at most one-for-one. That said, the evidence is not statistically significant and should be interpreted with caution.

Moreover, other factors could explain these findings, such as a change in the nature of the shocks driving costs. More work and potentially more data will be needed to better assess this question. Still, this work highlights the potential value of these linked firm-prices data in examining important macroeconomic questions.

Table 2: Regression of Price Changes on Margins

	(1)	(2)
Price change	-0.147***	-0.137
	(0.044)	(0.225)
Price change*2019		0.0235
		(0.261)
Price change*2020		0.056
		(0.245)
Price change*2021		-0.178
		(0.241)
Price change*2022		0.102
		(0.243)
	0.015	0.047
	742	742

Note: Regressions include controls for year. Includes firms with reported input costs (so excludes smaller businesses). Regressions done at Enterprise Group level.

Further work is needed to further refine the above metrics and explore other aspects of the data such as the size and frequency of discounting activity. But the above results highlight the significant value that prices microdata can potentially provide in helping policymakers to better understand and monitor inflation dynamics. The data will become even more valuable over time as the sample become longer (and potentially broader), and as more detail is provided on the nature of measured items. Expanding the availability of other prices data sets, such as producer price data or data underlying the CPI, would also add significant value as they would expand the set of sectors that can be considered. This would be the case even if this data can't all be linked to BLADE. As the integration project matures, combining it with other BLADE integration projects could also expand the set of questions that could be examined. For example, combining prices data with WPI microdata or Workplace Agreements Database integrations could provide scope to examine the pass-through of wage increases to prices.

6. Future directions and collaboration

The recent sharp increase in inflation across the globe has reinforced how important it is for policymakers to be able to monitor and understand the drivers of nominal variables like prices, wages, and incomes. Work by the ABS and others to open up access and integrate various new data sources has significantly increased the scope for policymakers to do this, allowing them to formulate better evidenced-based policies.

Many of these databases are new, and their value will continue to grow as samples become longer and more policymakers and researchers have the opportunity to draw out insights. But, as discussed, there are some low-cost ways to potentially increase the value of this data further. For example, bringing together some of the existing disparate integration projects could allow policymakers to exploit synergies between them. This is also likely to increase the number of policymakers and researchers working on the datasets, increasing scope for new insights to be drawn. Further integration of existing data assets could also be extremely valuable where feasible, such as integrating the L-LFS with STP/MADIP or opening up and integrating more prices microdata. Though new integration projects obviously have higher costs and so would need to be assessed and prioritised.

Private sector data sources are also likely to provide additional insights that can help inform policymakers, given they cover key topics and concepts that are not typically covered by administrative data and costly to collect through surveys, such as household level consumption and firm-level sales quantities. Such data sets played an important role in helping to inform the Government's COVID-19 response (Hambur *et al* 2022; Shergold *et al* 2022; Gruen 2022). Continuing to explore data sharing models and partnerships that open these private sector datasets and their insights to policymakers has the potential to significantly improve policymaking in Australia, and therefore the welfare of the Australian people.

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